# DISPERSION PREDICTION MODELS IN NESTED DATA STRUCTURES: EXAMINING THE PERFORMANCE OF DISPERSION INDEXES IN POLYTOMOUS ITEMS

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**DISPERSION PREDICTION MODELS IN NESTED DATA STRUCTURES: EXAMINING THE PERFORMANCE OF DISPERSION INDEXES IN POLYTOMOUS ITEMS**

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This study was designed to explore two possible causes of and solutions to poor dispersion prediction model performance in polytomous items. First, the impact of the correlation between the 'level' (e.g., the average score of the distribution) and the 'strength' (the dispersion among the data points in a distribution) on the dispersion effect was explored. Second, the extent to which non-linearity and heteroscedasticity influenced the dispersion effect was also explored. In order to explore these two factors, Monte Carlo studies were performed in which the dispersion index, the number of aggregated observations, the number of nested data points, the number of items from which the dispersion index was derived, the shape of the distribution, and the 'level' covariate in the multiple regression model were varied. The studies used a 5 point response polytomous item context. The evaluation criteria included power/Type I error rates, model $R^2$, $sr^2$ for the dispersion index, the VIF of the dispersion index, linearity of the dispersion index, and homoscedasticity of the errors in the dispersion prediction model.

The results suggest that none of the dispersion indexes systematically violate the multiple regression assumptions of linearity or homoscedasticity. They also suggest that the choice of the dispersion index, the number of items used, and the central tendency covariate used in the

dispersion prediction model are the prominent determinants of good performance in a 5 point response scale polytomous item context. The sample standard deviation (*SD*) and average deviation indexes (*ADm* and *ADmd*) performed equally well and substantially better than the *MAD*, *CV*, and *awg* in terms of the evaluation criteria across the conditions of the study. The performance of the *SD*, *ADm*, and *ADmd* improved substantially when computed from 5 different polytomous items as opposed to a single polytomous item. Finally, the results suggest that in skewed distributions the performance of the *SD*, *ADm*, and *ADmd* decreases due to an increased correlation with the level covariate. This decrease in performance can be counteracted in skewed distribution by controlling for the median as the level covariate as opposed to the mean.

## TABLE OF CONTENTS

## LIST OF TABLES

## LIST OF FIGURES

## PREFACE

The following dissertation benefitted greatly from the valuable insight of the members who served on my dissertation committee: Dr. Feifei Ye, Dr. Kevin Kim, Dr. Clement Stone, and Dr. John Mendeloff. I extend special thanks to my advisor, Dr. Feifei Ye, who has provided me with tremendous support and friendship throughout my doctoral studies.

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# 1.0 INTRODUCTION

## 1.1 STATEMENT OF THE PROBLEM

Nested data structures commonly exist in studies focusing on naturally occurring groups of people (i.e., workgroups and classrooms) and those that involve individuals with a longitudinal or repeated measures design. The analysis of nested data structures has been a topic of interest for statisticians and research design theorists for decades. Analysis strategies can take on numerous forms which include disaggregation, aggregation, and hierarchical linear modeling (HLM). Disaggregation methods have been largely discounted due to the fact that most statistical tests assume independence between observations. Aggregation methods statistically summarize the nested data points into a single score used to represent a workgroup or classroom in the case of a 'group' study or an individual observation in the case of a 'within-person, longitudinal' study. Although aggregation strategies eliminate the dependence between observations, they are less efficient in the sense that important information and statistical power is lost. Raudenbush and Bryk (2002) suggested that by aggregating lower-level observations upward, "we throw away all the within-group information, which may be as much as 80% to 90% of the total variation before we start the analysis" (p. xx). By statistically accounting for the dependence between observations in nested data structures, the HLM strategy enables both the higher-order variables and lower-level nested observations to be entered into the statistical model simultaneously. By retaining all available information, the HLM strategy has some advantages over available aggregation methods.

New theoretical developments across academic disciplines, however, have challenged the traditional ways of analyzing nested data structures. Specifically, there is an increased interest across academic disciplines in using the within group variability as a theoretical construct in and of itself (Chan, 1998; Chen, Mathieu, & Bliese, 2004; Kozlowski & Klein, 2000). Measures of within group variability are increasingly used as an outcome, moderator, and predictor of outcomes in the organizational, psychological assessment, cognitive achievement, and medical sciences. For the purpose of this study these models are referred to as *dispersion models.* Of particular interest in this study is dispersion models that use the dispersion construct as a predictor of important group level outcomes in multiple regression models; herein referred to as *dispersion prediction models*. Dispersion prediction models are appropriate when research questions center on how the variability among individuals in naturally occurring groups, or among data-points corresponding to an individual over time, can influence group-level and individual-level outcomes respectively.

Traditional nested data analysis approaches view the within group variance as measurement error or 'noise' around a single true score (i.e., the average of the nested data points) (Chan, 1998; Golay, Fagot, & Lecerf, 2013). As the 'error' within a set of nested observations increases, confidence in and the meaningfulness of the true score decreases. Therefore, traditional aggregation methods have developed sophisticated statistical indexes and corresponding 'cut-off' rules to be used when aggregating nested observations to a higher level (LeBreton & Senter, 2008). By providing within-group variance components, HLM can be used to study this variability as an outcome of interest. However no existing mechanism in the HLM framework allows this within-group variance component to predict higher-order group based outcomes.

Thus, the prominent approach to study dispersion prediction models is aggregation of the nested data points to the higher-level through a statistic that captures the degree of within-group variability. Because this analysis strategy differs from traditional aggregation techniques, methodological questions regarding the use of dispersion indexes in multiple regression models needs to be answered (Cole, Bedeian, Hirschfeld, & Vogel, 2011; Roberson, Sturman, & Simons, 2007).

Evidence that dispersion prediction models are not well understood from a methodological perspective can also be gleaned from a review of the existing empirical investigations. A thorough review of the dispersion model literature was conducted across academic disciplines in an effort to determine if patterns existed between studies that found a significant effect for the dispersion construct and those that failed to. Within the organizational sciences, 'climate strength' (i.e., the extent to which individuals in a group share an interpretation of relevant policies, practices, procedures, and goals and develop shared perceptions about what behaviors are expected and rewarded) is the dispersion model most often used (Roberson et al., 2007). Based on a review of the organizational literature, operationalized dispersion prediction model studies consistently fail to detect a significant effect. In contrast to the poor dispersion model performance in the organizational science context, when used as a predictor in other academic contexts, operationalized dispersion constructs are consistently a significant predictor of important outcomes. Within psychological, cognitive, and ability assessments research, intra-individual variability over time on a variety of measures (e.g., self-esteem, core self-evaluations, reaction time, cognitive ability tests and assessments, etc.) has been used to predict outcomes such as suicide attempts, depression, emotional distress, diagnosed developmental disorders, and long-term cognitive performance (e.g., Hultsch, MacDonald, Hunter, Levy-Bencheton, & Strauss, 2000; Nesselroade & Salthouse, 2004). Dispersion models have also been operationalized within the medical sciences. Researchers have investigated the extent to which intra-individual variability of health indicators (e.g., blood pressure, breathing, and heart-rate) relates to important health outcomes such as ventilation separation success, stroke, heart attack, and cardiovascular disease (e.g., Rothwell et al., 2010; Wysocki et al., 2006). These studies consistently find a large and significant effect for the dispersion construct using indexes identical to those used in the organization sciences. These findings suggest that methodological issues related to its use may be the reasons behind such discrepancies. The broad reaching theoretical and practical importance of dispersion prediction models suggests that the potential causes are worthy of exploration.

Between these two different literatures overlap exists on important parameters, including the prominent indexes used to reflect the dispersion model construct, the number of nested data points, and the number of aggregated observations used in the multiple regression equation (i.e., groups or individuals). One substantial issue was noted however; nearly all non-significant dispersion prediction model studies exist in situations where the dispersion construct predictor was operationalized from a discrete interval type variables (also referred to sometimes as polytomous items and/or Likert rating scales) resulting in discrete interval distributions; while significant dispersion model studies mainly exist in variables that can be considered continuous.

Discrete interval distributions are characterized by a restricted and fixed number of potential scores (i.e., usually 5 or 7) between a lower and upper bound (i.e., usually 1 and 5 or 1 and 7). The continuous type distribution may be unbounded or theoretically and/or practically bounded on one or more of the end-points, but the probability of reaching the extreme score is rare due to: 1) extreme outcomes associated with observations at the endpoints (e.g., a zero heart-rate, or an extremely high blood-pressure); or 2) because the range of potential scores is so great (e.g., 1 - 100 or 1 - 1,500, etc.) that the statistical properties of the resulting distribution is markedly different from a polytomous type.

Simulation studies designed to explore the nature of dispersion prediction models are limited to one study (i.e., Roberson et al., 2007). Roberson et al, (2007) explored the relative performance of the sample standard deviation (*SD*), the $r_{WG}$, the $AD_M$, the $a_{WG}$, and the coefficient of variation *CV*. This study found that, regardless of the dispersion statistic used, the prediction of a group-level outcome by the group-level dispersion construct was prone to an inflated Type II error rate (across dispersion indexes the power for each of the dispersion indexes was approximately 20% when a large effect size was simulated). In their concluding statements, Roberson et al., (2007) suggested that dispersion model researchers should consider adjusting the significance to a level above the traditionally accepted .05. However, they also suggested that the search for reasons for low power in dispersion prediction model research should continue.

The goal of this study is to explore two factors which may potentially influence the performance of dispersion measures in dispersion prediction models within the context of discrete interval distributions. First, it is suggested that a correlation between the 'level' (distribution average score) and the 'strength' (distribution dispersion) can make it difficult to detect a significant regression coefficient for the dispersion effect in the dispersion prediction multiple regression model. Second, because the relationship between the level and strength of the nested data can be related in a non-linear fashion, there is a possibility that the dispersion construct and an outcome are also related in a non-linear fashion. Modeling a linear relationship, when the true relationship is nonlinear can make it difficult to detect a significant effect. Both of these issues, discussed briefly in sections 1.1.1 and 1.1.2, are suspected to influence the performance of dispersion prediction models in discrete interval distributions.

### 1.1.1 The Mean X Variance Correlation

Properly specified multiple regression models assume that the predictors are not strongly correlated. Where two predictors do share a strong statistical relationship the regression coefficients can become unstable and biased in terms of their magnitude (Lomax, 2007; Pedhazur, 1997; Wilcox, 2003). This mean x variance correlation can also inflate the standard error of the coefficients making it more difficult to detect significance (Lomax, 2007; Pedhazur, 1997; Wilcox, 2003).

Within a discrete interval distribution, the distribution mean and variance are dependent. Because the mean and variance are related in a non-linear manner (where the max variance is expected at the distributions midpoint and is minimized at the scale extreme scores) the correlation between the mean and variance in an aggregated dataset (in terms of its strength and direction) depends on where the overall average score falls within the potential range of the variable's distribution across the aggregated observations. When the overall mean across observations is within the lower half of the scale, a strong positive correlation is expected. Conversely, when the overall mean is within the upper half of the scale, a strong negative correlation is expected. When the mean of the overall distribution is at the middle of the variable's range, the correlation can be negative, positive, or zero depending on the interaction between mean and variance in the individual observations.

Although the direction of the relationship is most likely of little consequence, the magnitude of the correlation between the mean and variance might be. As is recommended and common in dispersion model research (Cole et al., 2011), the distribution's level (e.g., average score) should be included as a covariate in the multiple regression model. High correlations between the level covariate and dispersion predictor could be the cause of small, statistically insignificant incremental effects of the dispersion construct.

To further complicate this issue, in discrete interval distributions there is an increased probability of the resulting distribution to be skewed. Discrete interval type variables are bounded on either side of the distribution creating a floor and ceiling effect. These variables also typically require that an individual provide perceptual ratings of a stimulus (e.g., organizational or classroom environments). Due to the pervasiveness of cognitive and affective biases, theory and research suggest that distributions commonly encountered in organizational research tend to vary greatly in shape. Although non-normal skewed distributions can exist in any academic context (Micceri, 1989), researchers and theorists suggest that perceptions of nested individuals are most often consistent due to social influence processes and/or biased because of psychological leniency or severity (LeBreton & Senter, 2008).

Skewed distributions may decrease the performance of dispersion prediction models in discrete interval distributions in several distinct ways: 1) the performance of dispersion indexes may not be robust to adequately deal with skewed distributions; or 2) the reliability (and even interpretability) of many of the indexes that can be used to reflect the dispersion construct breaks down as the mean reaches the lower or upper bounds of a distribution of scores (as in extremely skewed discrete interval distributions); and, of primary interest in the current study, 3) because of attrition of the upper or lower half of the response scale in a skewed discrete interval distribution at least a moderate correlation between the distribution mean and dispersion can be expected. In essence, as will be discussed, a skewed discrete interval distribution almost certainly guarantees a moderate correlation between the distribution's average score and its variance further increasing the difficulty of finding a significant effect for the dispersion construct of interest.

### 1.1.2 The Multiple Regression Assumption of Linearity

An important assumption of multiple regression is that both the predictor and outcome are linearly related. If this assumption is violated, and a linear regression is performed, the strength of the relationship between the two can be underestimated (Lomax, 2007; Pedhazur, 1997; Wilcox, 2003). Further, a linear model fit to a nonlinear relationship can increase the likelihood of violating the linear regression assumption of homoscedasticity. This can cause the standard error to be inflated making it even more difficult to find a significant effect for the regression coefficient.

Evidence derived from existing empirical research suggests that a dispersion construct and an outcome may be prone to a nonlinear relationship (Cole et al., 2011; Dineen, Noe, Shaw, Duffy, & Wiethoff, 2007; Lindell & Brandt, 2000). Lindell and Brandt (2000) suggested that if a group mean and a group level outcome are linearly related, and the group mean and group dispersion are non-linearly related, there is a possibility for the group dispersion and the group level outcome to be nonlinearly related as well. Dineen et al., (2007) explored Lindell and

Brandt's (2000) assertion by executing a polynomial dispersion prediction model in two distinct studies and found that in one study the quadratic term was not significant, but in the other it was.

In order to explore whether or not the two possible causes outlined above influence the performance of dispersion models in discrete interval distributions, Monte Carlo simulations were performed. In order to reflect the use of polytomous items in the organizational context, a 5 point polytomous scale was considered. The first goal of this study was to determine if the different dispersion indexes present nonlinearity between the dispersion construct and an outcome and/or violate the assumption of homoscedasticity in the dispersion prediction model. The second goal of the study was to determine the influence of the correlation between the 'level' and 'strength' in the multiple regression dispersion prediction model. The correlation between the 'level' and 'strength' is realized by varying the skewness of the distribution of the 5-point polytomous item between normal, moderate, and heavy skew. In addition, three factors that theoretically influence the 'level'/'strength' correlation and potentially improve the performance of dispersion prediction models across the levels of distribution shape were considered. First, both mean and median based dispersion indexes were included in the studies. Second, in addition to using the distribution's average score as the 'level' covariate in the multiple regression model, the distribution's median was also considered. Thus, an assessment of performance between patterns of dispersion index (mean vs. median based)—level covariate (mean vs. median) could be made. Finally, in order to increase the potential variability between the upper and lower bound of the polytomous distribution, each of the dispersion indexes were calculated from both 1 and 5 items.

Each of the simulations was designed such that the relationship between the dispersion among a set of nested scores and an outcome was set to vary in specified effect size. In addition, the number of aggregated observations and the number of nested data points were also set to vary by specified levels. The performance of different dispersion indexes across the these parameters and their levels were evaluated using the $R^2$ for the complete model (i.e., the mean and the dispersion index in the prediction of the generated outcome), the $sr^2$ for the unique effect of the dispersion index on the outcome, power and Type I error rates, and a variance inflation factor (VIF) for the slope of the dispersion index regression coefficient.

## 1.2 RESEARCH QUESTIONS

Specifically, the research questions of the current study can be stated as follows:

1. Do the dispersion indexes present nonlinearity and / or heteroscedasticity in dispersion prediction multiple regression model in a polytomous item context?

2. To what extent does the correlation between the dispersion index and the level covariate in dispersion prediction multiple regression models impact their performance in a polytomous item context? More specifically, the questions are:

2.1. Does the dispersion index computed from a skewed distribution affect the performance of the dispersion index in dispersion prediction model?

2.2. Does the dispersion index computed from 5 polytomous items improve performance over those calculated from 1 polytomous item?

2.3. Does the use of median as the level covariate improve the performance of the dispersion index when compared to models that use the mean as the level covariate?

2.4. Is there difference among the dispersion index in their performance and is such difference dependent on the distribution shape, the number of items used to calculate the dispersion index, and the use of mean or median as the 'level' covariate?

## 1.3 SIGNIFICANCE OF THE STUDY

The broad reaching theoretical and practical importance of dispersion prediction models suggests that existing methodological issues related to its use in discrete interval distributions and the reasons behind such discrepancies are worthy of exploration. Generally, determining whether or not methodological reasons are the source of the consistent rejection of hypotheses related to dispersion models in discrete interval variable contexts is of critical importance. In other words, are disconfirmed hypotheses the result of poor theory or poor methodology? If it is due to methodology, what are the causes and potential solutions for the low power? By exploring a variety of potential remedies (e.g., through a carefully chosen dispersion index, controlling for the 'level' in creative ways, or increasing the potential variability of the scale through multiple items) the results of this study can have a direct impact on the methodological issues that applied researchers are faced with when executing empirical dispersion prediction models studies using polytomous items.

In addition to answering these fundamental questions, numerous other benefits are expected that apply to a broader academic audience. The potential impact of non-normal skew on dispersion prediction model performance has not been previously evaluated. This study takes a creative approach to determine the most effective performing dispersion prediction models in skewed distributions by varying both mean based and median based estimators of dispersion and using both the mean and median as the level covariate in the multiple regression model. By assessing the performance of dispersion prediction models that vary based on a number of important factors in both normal and skewed distributions, the results will provide methodological guidance to a wide range of potential issues applicable to these models in discrete interval distribution contexts.

# 2.0 REVIEW OF THE LITERATURE

## 2.1 DISPERSION MODELS ACROSS ACADEMIC DISCIPLINES

Across empirical studies conducted within distinct academic disciplines there are discrepancies in the results of statistical tests of dispersion prediction models. Within the organizational sciences, 'climate strength' (i.e., the extent to which individuals in a group share an interpretation of relevant policies, practices, procedures, and goals and develop shared perceptions about what behaviors are expected and rewarded) is the dispersion model most often used. Based on a review of the organizational literature, dispersion prediction model studies consistently fail to detect a significant effect.

In contrast to the poor dispersion model performance in the organization science context, when used as a predictor in other academic contexts, operationalized dispersion constructs are a consistently significant predictor of important outcomes. Within psychological, cognitive, and ability assessments research, intra-individual variability over time on a variety of measures (e.g., self-esteem, core self-evaluations, reaction time, cognitive ability tests and assessments, etc.) has been used to predict outcomes such as suicide attempts, depression, emotional distress, diagnosed developmental disorders, and long-term cognitive performance (e.g., Hultsch, MacDonald, Hunter, Levy-Bencheton, & Strauss, 2000; Nesselroade & Salthouse, 2004). Researchers within the medical sciences have investigated the extent to which intra-individual variability of health indicators (e.g., blood pressure, breathing, and heart-rate) relates to important health outcomes such as ventilation separation success, stroke, heart attack, and cardiovascular disease and consistently find a large and significant effect for the dispersion construct using indexes identical to those used in the organization sciences (e.g., Rothwell et al., 2010; Wysocki et al., 2006).

In the following two sections the dispersion model literature will be discussed; first from an organizational science perspective and then from a psychological assessment, cognitive performance, ability assessment, and medical science perspective.

### 2.1.1 Organizational Science Dispersion Models

Within the organizational science academic disciplines multilevel theory has been used to provide a framework around different types of group level constructs and their associated measurement and analysis strategies. An important aspect of this classification scheme is the explicit recognition of the difference between the level of measurement and the level of analysis (Hitt et al, 2007; Klein, Dansereau, & Hall, 1994; Rousseau, 1985). Rousseau (1985) defined the level of measurement as "the unit to which the data are directly attached" and the level of analysis as "the unit to which the data are assigned for hypothesis testing and statistical analysis" (p. 4). With this recognition comes the realization that group level theoretical constructs can be measured at a lower level. To that end, a general distinction can be made between group level constructs that are measured at a lower level (emergent, bottom-up group-level constructs) and those that are measured at the same level (global, top-down group-level constructs) (Kozlowski & Klein, 2000; Klein & Kozlowski, 2000; Chen et al., 2004).

Global group level constructs (also known as aggregate models by Chen et al, 2004) can be described as objective, descriptive and observable characteristics of a group (Klein & Kozlowski, 2000). Distinct from bottom-up processes which form emergent group level constructs, global group level constructs do not originate (or emerge) from individual characteristics. Rather, they are independent of individual perceptions, attitudes, behaviors, or other characteristics and can be seen as a representation of the unitary group (Klein & Kozlowski, 2000). In the case of global group level constructs the level of measurement and analysis are consistent and both exist at the group level at which hypotheses are derived (Chen et al, 2004). Global group level constructs can be further conceptualized as those that can vary between groups but do not vary within groups (Bliese & Jex, 2002). Group function, group size, and strategic or administrative policies and programs all can be conceptualized as global group-level constructs (Bliese & Jex, 2002; Klein & Kozlowski, 2000).

In contrast with global group level constructs, emergent group level constructs are derived from the aggregation of observed characteristics of individual group members. Rather than being independent of the individual characteristics of group-members, emergent group level phenomena are tied to, integrated with, and dependent on these individual level observations (Chen et al, 2004; Kozlowski & Klein, 2000). The role of within group variance is distinct between global and emergent group level phenomena. Global constructs are fixed at the group level (i.e., the same for each member within the group) and emergent constructs can vary among the individuals that comprise the group. Various facets of group level climate, group knowledge or intelligence, and group efficacy are examples of emergent group level phenomena.

Because of the fundamental measurement distinction between global (where the measurement and analysis levels are equivalent) and emergent group level constructs (where the level of measurement differs from the level of analysis), validity issues concerning the two types are also very different. Further, the distinct types of emergent group level constructs that have been identified in the multilevel literature require distinct types of construct validity evidence.

As a first step in determining which type of validity evidence is important for a given type of emergent construct, multilevel theorists recommend that the process through which an individually measured characteristic combines to become a group level construct be identified (Hitt et al, 2007; Chen et al, 2004; Kozlowski and Klein, 2000). Multilevel theory suggests that two distinct processes can be used to describe the mechanism through which a group level construct is formed from individual level observations: compilation and composition.

In compilation processes of emergence the group level construct shares little theoretical similarity with the individual level scores (Bliese & Jex, 2002; Hitt et al 2007; Kozlowski & Klein, 2000). For compilation processes individually collected measures are combined in complex, nonlinear ways that yields a group level construct which cannot be reduced to the parts which comprise it (Hitt et al, 2007). An example of an emergent type of construct based on the process compilation is the selected score model (Chen et al, 2004). Selected score group level constructs may be based on a single observation within the group (e.g. where the group construct is determined by the smartest, fastest, slowest, or weakest member of the group) (Chen et al, 2004; Kozlowski and Klein, 2000). In this example, the validity of the group level construct is based on the accuracy of an appropriately identified individual level observation.

Composition processes are grounded on the premise that the group and individual level content is same but are qualitatively different at different levels of analysis (e.g. psychological climate can emerge to form group level climate) (Hitt et al, 2007). In composition processes equal weight is placed on each observation, and the group level constructs which emerge from this processes can be represented by simple descriptive statistics (e.g. mean, variance, sum) (Hitt et al, 2007). Because measurement of group level constructs based on emergent composition models possess isomorphic properties, multilevel theorists and researchers have developed frameworks to understand the types of validity evidence necessary to support aggregation.

The types of emergent composition models that have been theoretically proposed and generally accepted within the multilevel literature are: summary index models, consensus models, reference shift models, and dispersion models (Chen et al, 2004; Kozlowski & Klein, 2000; and Chan, 1998)[1]. The type of validity evidence suggested for each of these distinct emergent composition models is based primarily on how dispersion among the individual observations is treated; as irrelevant variance, important measurement error; or the key construct itself.

#### 2.1.1.1 Summary Index Models

In summary index models individual observations are summated or averaged to represent the group level construct without regard given to the variance among the individual observations (Chen et al, 2004; Chan, 1998). This type of composition model has also been referred to as 'additive' (Chan, 1998) and as 'pooled unconstrained' (Kozlowski and Klein, 2000). Chan (1998) suggests that psychological climate can be aggregated to group level climate under this

[1] These types were chosen based on their generalized acceptance and consistent definitions across multilevel theorists. Terminologies for these emergent composition models were chosen based on the summarizing work of Chan et al (2004).

theoretical model when the researcher "stipulates that all organizations have an organizational climate that can be described as high or low on various dimensions regardless of the level of within-organization [or group] individual-level agreement" (p. 237). The summary index model assumes variance around the aggregate score (i.e. the mean) to be of little substantive meaning, and instead is an uneventful source of measurement error (Chan, 1998).

#### 2.1.1.2 Consensus and Referent Shift Models

In contrast to the summary index model, empirical work conducted within the consensus and referent shift models consider the level of within group agreement as a critical validity component of the group level construct. Consensus models (Chen et al, 2004) may also be referred to as 'pooled constrained' (Kozlowski & Klein, 2000) and as 'direct consensus' (Chan, 1998). Consensus models are evaluated at the individual level using measurement items which refer to the individual in question (e.g. 'I exhibit the following properties' or 'I am innovative at work').

Referent shift models, also known as convergent (Kozlowski & Klein, 2000) and as 'referent-shift consensus' (Chan, 1998) are similar to consensus models in the requirement of within group agreement to justify aggregation, however, there is a shift in referent prior to measurement (e.g. 'my work group exhibits the following properties' and 'the members of my team are innovative').

### 2.1.1.3 Dispersion Models in Organizational Research

A more recently acknowledged type of composition emergence model is the dispersion composition model. The dispersion model differs from the previously discussed composition models (i.e., summary index, consensus, and referent shift) in that the agreement and or dispersion among the individual level scores within the group is itself the group-level construct. Instead of using statistical measures of interrater agreement and / or dispersion as a means to validate the group-level construct, the dispersion model uses these statistics to represent the group-level construct.

Chan (1998) suggests that in contrast to the validity evidence of within group agreement for consensus and reference shift models, dispersion models require a very different form of validity evidence. Chan (1998) suggests that for a dispersion model to be operationalized as a valid group-level construct it should not be used in the presence of multiple distinct groups. Thus, using the dispersion composition model as a group-level construct that combines two distinct groups is a threat to its construct validity. Chan (1998) goes on to suggest that the statistical evidence necessary to support the validity of the construct is a distribution of individual level scores that is unimodal. In other words, for dispersion composition models "the prerequisite is the absence of multimodality in the within-group distributions of lower level scores" (p. 240). He goes on to state that:

> When there is multimodality, it is possible that the variance or dispersion along the original grouping variable does not represent a meaningful dispersion construct. One may have to move downward from the group level to the subgroup level to identify any potentially meaningful subgrouping variable corresponding to the multimodal responses (p. 240).

If properly justified, methodologically the variability in individual ratings of the climate measure then becomes the source of a key construct in the multi-level model which can be used to predict both individual level person variables (e.g. behavior, performance, learning, perceptions, motivation, attitudes, etc.) and group level variables (e.g. group learning, group performance, group motivation, etc.).

Within the organizational sciences, dispersion models are most often operationalized under the theory of climate strength. Climate strength theory is the operationalized dispersion model for the many different facets of organizational / group climate within the social psychology and organizational behavior disciplines (Schneider, Salvaggio, and Subirats, 2002).

Climate strength theory is grounded in Mischel's (1973) distinction between strong and weak contextual variables. Mischel (1973) argues that contexts are powerful to the extent that they: 1) lead all individuals within the group to construe the particular context in the same way; 2) induce uniform expectancies regarding the most appropriate response pattern and provide adequate incentives for the performance of that response pattern; and 3) instill the skills necessary for its satisfactory construction and execution. Mischel (1973) goes on to argue that individuals have increasing control over personal responses when a given context is weak and unstructured. When situational variables are unstructured any personal response is equally likely and variance of individual differences will be greatest. Conversely, when situational variables are strong and structured, a limited number of reinforced responses are appropriate and variability between personal responses will be minimized.

A dispersion model of climate, operationalized as climate strength (Schneider et al, 2002) suggests that there can be a distinction between strong climates (those with less variability in individual perceptions of climate measurement items) and weak climates (those with excess variability in individual perceptions of climate). Strong climates give way to homogeneous sets of perceptions while weak climates allows for heterogeneity in these perceptions. The notion of climate strength theory suggests, then, that the agreement or dispersion of individual responses within a collective will be related to individual and collective outcomes in hypothesized ways (e.g. strong climates will lead to uniform effective behaviors and increased group performance).

Since the composition typology work of Chan (1998), academic interest in the dispersion model of emergence has grown considerably. Since Chan (1998) numerous empirical studies using the climate strength operationalization have been published. Table 1 presents these studies.

Although supported by strong and intriguing theory, as can be seen from the 'Findings' column in Table 1, the results of empirical conclusions drawn from hypotheses grounded in the climate strength dispersion composition model have been, at best, mixed. As is reflected in the table, the worst performing dispersion models are those in which the dispersion construct was used as a predictor in a multiple regression model.

Table 1: Dispersion model empirical studies in the organizational sciences

| Authors | Dispersion Construct | Dispersion variable in research model | Number of items, number of scale points | Number of Nested Data Points | Number of Aggregated Observations | Level of analysis | Dispersion Statistic Used | Findings | Correlation between Mean and Dispersion |
|---|---|---|---|---|---|---|---|---|---|
| Colquitt, Noe, and Jackson, 2002 | Climate Strength (justice) | Outcome[a] Moderator[b] Predictor[c] | 7 items 5 scale points | ~20 | 88 | Group level | CV | a-mixed b-support c-no support | Not provided |
| Dawson, Gonzalez-Roma, Davis, and West, 2008 | Climate Strength (well-being, quality and integration) | Moderator[a] Predictor[b] | ~5 items for each dimension, 5 scale points | ~212 | 56 | Group level | $AD_M$ | a-no support b-mixed | -.33, -.14, -.19 |
| Dickson, Resick, and Hanges, 2006 | Climate Strength (organic and mechanistic) | Correlate | ~10 items for each dimension, 7 scale points | 15-228 | 123 | Group level | SD | mixed | -.22 |
| Gonzalez-Roma, Fortes-Ferreira, and Peiro, 2009 | Climate strength (support, innovation, goal achievement, enabling) | Moderator | 4 items for each dimension, 6 scale points | 5 | 155 | Group level | $AD_M$ | mixed | .43, .50, .50, .37 |
| Gonzalez-Roma, Peiro, and Tordera, 2002 | Climate strength (support, innovation, goal orientation) | Outcome[a] Moderator[b] | 3 items for each dimension, 5 scale points | 3-5 | 197 | Group level | $AD_M$ | a-mixed b-mixed | .55, .27, .20 |
| Grizzle, Zablah, Brown, Mowen, and Lee, 2009 | Climate strength (customer service) | Moderator | 6 items, 5 scale points | ~18 | 38 | Cross level | SD | mixed | -.40 |
| Klein, Conn, Smith, Sorra, 2001 | Strength of perceptions of work environment (innovativeness, resource availability) | Outcome | 5 items for each scale, 5 scale points | ~6 | 65 | Group level | SD | support | Not provided |
| Lindell and Brandt, 2000 | Climate consensus (leadership) | Correlate[a] Predictor[b] | 3 items, 5 scale points | ~7 | 180 | Group level | $SD^2$ | a-mixed b-no support | -.50 to -.20, average = |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mediator[c] | | | | | | c-no support | -.32 |
| Moliner et al, 2005 | Climate Strength (distributive, procedural, interactional justice) | Moderator[a] Predictor[b] | ~4 items per dimension, 7 scale points | ~3 | 108 | Group level | $AD_M$ | a-mixed b-mixed | -.06, .20, .62 |
| Naumann and Bennett, 2000 | Climate Strength (justice) | Outcome | 9 items 5 scale points | 3 to 14 | 34 | Group level | $r_{WG}$ | support | Not provided |
| Roberson, 2006 | Climate strength (justice) | Outcome | 4 items 9 scale points | 3 | 124 | Group level | SD | support | Not provided |
| Schneider, Salvaggio, and Subrirats (2002) | Climate Strength (customer service) | Moderator[a] Predictor[b] | ~5 items for each dimension, Not reported | ~16 per group | 134 | Group level | SD | a-support b-no support | Not provided |
| Sowinski, Fortmann, and Lezotte, 2008 | Climate Strength (customer service) | Moderator | 5 items, 5 scale points | ~6 | 129 | Group level | SD | no support | -.35, -.46 |
| Zohar and Luria, 2005 | Climate Strength (safety) | Outcome | 25 items, 5 scale points | ~30 | 81 | Group level | SD | support | .51 |
| Zohar and Tenne-Gazit, 2008 | Climate strength | Outcome | 6 items, 5 scale points | 30 | 45 | Group level | SD | support | Not provided |
| Lingard, Cooke, and Blismas, 2010 | Climate Strength (safety) | Correlate[a] Predictor[b] | 11 items, 5 scale points | ~5, ~11, ~9 | 15, 9, 16 | Group level | $r_{WG}$ | a-support b-mixed | .44, .50 |

Note: All dispersion indexes are derived from discrete interval distributions. In reference to the terms used in the far right, ‘Findings’ column: ‘support’ refers to an empirical study in which all hypotheses tests related to the dispersion construct of interest were significant and in the direction predicted; ‘no support’ none of the hypothesis tests were found to be significant; and ‘mixed’ at least one hypothesis test was significant and one hypothesis test was not significant.

To date, one simulation study has been conducted in an effort to determine the causes of poor dispersion model performance in the organizational science context. Roberson et al, (2007) study was designed to explore whether or not the choice of statistic mattered. Roberson et al, (2007) conducted a simulation in which they operationalized the dispersion model of composition as climate strength in normally distributed, 7-point, Likert-type response scale variables. The authors simulated a scenario in which they were able to explore the differences between the performance of various dispersion indexes in terms of their recovery of the specified relationship between within group variance and a group-level outcome. In their study they included the *CV*, $r_{WG}$, $a_{WG}$, $AD_M$, and the *SD*. They varied the number of individuals nested within each group (3, 5, 10, 25); the number of groups (40, 80, 120); the base amount of individual observation variance to explained by the mean (0.00, 0.10, 0.30, 0.50); the variability of the base amount of variance (0.00, 0.10, 0.30, 0.50); and the relationship between the group-level outcome and the mean ($\beta_1$), variance ($\beta_2$), and mean X variance ($\beta_3$) interaction (each 0.00, 0.10, 0.30, 0.50).[2]

Roberson et al (2007) found that, across all simulation parameters, the correlation between the agreement / dispersion statistics ranged from .80 to 1.00 with an average of .912 showing that the statistics consistently rank order the variation of individual scores across groups. After assessing the relationships between the various dispersion and agreement statistics, the authors then assessed the efficiency with which the statistics recovered the specified relationships in terms of the frequency with which they committed Type I and Type II errors.

[2] Because of the dependence between the mean and variance in discrete interval variables, when studying dispersion models in this context, researchers typically control for the average score when conducting research on the topic. When researchers consider the dispersion as a moderator of the relationship between the mean and a group level outcome an interaction term is included (Cole, Bedeian, Hirschfeld, & Vogel, 2011).

Because there were so many potential combinations (i.e., 12,288) for each dispersion statistic under investigation the authors compared the average frequency with which significance was detected across simulation parameters. Overall, they found that when a large dispersion effect was specified in the research model that controlled for the average score (and in those that controlled for the average score and the interaction term), each of the dispersion/agreement statistics displayed a relatively low probability of recovering a significant regression coefficient: $CV$ = 16.5%; $r_{WG}$ = 23.8%; $r^*_{WG}$ = 23.8%; $a_{WG}$ = 22.1%; $AD_M$ = 23.7%; and the $SD$ = 24.4%.

The extent of their overall findings, then, confirm the problematic use of dispersion prediction models in the context of climate strength theory without offering evidence as to the potential factors which may have influenced these results. Thus, the reasons why dispersion prediction models perform poorly in organizational research remain elusive.

### 2.1.2 Comparison with dispersion models in other academic disciplines

Interestingly, dispersion model research conducted in academic disciplines outside of the organizational sciences has not suffered from the same methodological problems. Undergirded by strong theoretical arguments, researchers interested in psychological assessment, cognitive achievement, ability assessments and in the medical sciences have questioned the traditional notion of intra-individual variability as measurement error. In doing so there is increasingly convincing evidence that intra-individual variability is an important 'signal' of many important phenomena and not 'noise' around true level (Golay et al., 2013). Table 2 presents the details of some of these studies in a table formatted similar to Table 1.

Table 2: Dispersion model empirical studies in the psychological, cognitive and ability assessments, and the medical sciences

| Authors | Dispersion Construct | Dispersion variable in research model | Number of Nested Data Points | Number of Aggregated Observations | Level of analysis | Dispersion Statistic Used | Findings | Correlation between Mean and Dispersion |
|---|---|---|---|---|---|---|---|---|
| Witte et al, 2005 | Suicidal Ideation | Predictor | 20-28 | 108 | Individual | Mean Square Successive Difference (MSSD) | Support | Not Provided |
| Stuss et al, 2003 | Cognitive Performance | Outcome | 50-100 | 36 | Individual | SD and CV* | Support | Not Provided |
| Hata et al, 2002 | Blood Pressure | Predictor | Unclear / Variable** | 139 | Individual | CV | Support | Not Provided |
| Hata et al, 2000 | Blood Pressure | Predictor | Unclear / Variable** | 171 | Individual | CV | Support | Not Provided |
| Wysocki et al, 2006 | Breathing | Predictor | Unclear / Variable*** | 51 | Individual | CV | Support | Not Provided |
| Nesselroade & Salthouse, 2004 | Perceptual-Motor Performance | Outcome | 3 | 204 | Individual | SD | Support | Not Provided |
| Hultsch et al, 2002 | Cognitive Ability & Reaction Time | Outcome | 4 | 862 | Individual | SD | Support | Not Provided |
| Wojtowicz et al, 2012 | Cognitive Performance | Predictor | 30 | 36 | Individual | SD, CV* | Support | Not Provided |
| Rothwell et al, 2010a | Blood Pressure | Predictor | 10 | 2500, 3150, 2011 | Individual | SD, CV, Zeta[t] | Support | Not Provided |
| Rothwell et al, 2010b | Blood Pressure | Predictor | >5 | 19,257 | Individual | SD, CV, Zeta[t] | Support | Not Provided |
| Kikuya et al, 2008 | Blood Pressure | Predictor | ~26 | 2,455 | Individual | SD | Support | Not Provided |
| Eguchi et al, 2008 | Blood Pressure | Predictor | 12 | 300 | Individual | SD | Support | Not Provided |
| Hultsch et al, 2000 | Cognitive Performance | Predictor | 4 | 45 | Individual | SD, CV* | Support | Not Provided |
| Geurts et al, 2008 | Behavioral, cognitive, psychological responses | Predictor | 64 | 334 | Individual | SD | Support | Not Provided |

NOTE: all studies derived within a continuous type distribution. * = no differences found between the performance of the SD, CV, and modified. ** = readings recorded at every office visit over a 1-year time period. *** = every breath for 60 minutes. [t] significant different found between SD, CV; where CV more powerful predictor than SD; and Zeta is a more power predictor than the CV.

The dispersion predictor model studies reported in Table 2 use intra-individual variability over time on a variety of measures (e.g., self-esteem, core self-evaluations, reaction time, cognitive ability tests and assessments, heart rate, blood pressure, breathing etc.) to predict outcomes such as suicide attempts, depression, emotional distress, diagnosed developmental disorders, long-term cognitive performance, and important medical outcomes. When operationalized as a predictor, the studies presented in Table 2 report conclusive evidence for a strong and significant effect of the dispersion construct.

Similarities and differences between Tables 1 and 2 can be gleaned. First, the number of nested data points are similar between Tables 1 and 2. Nested data points refer to the number of individuals within a group (for Table 1) or repeated measures over time for an individual (Table 2). Table 1 shows that the number of nested data points ranges from 3 to approximately 230. Table 2 shows that the number of nested data points ranges from 3 to approximately 100. There are also similar measures used between the two contexts. Table 1 shows that dispersion indexes used in dispersion prediction models include the standard deviation (*SD*), the coefficient of variation (*CV*), the average deviation around the mean ($AD_M$), and the rater within-group agreement index ($r_{WG}$). Table 2 shows that the *SD*, *CV*, and Zeta (ζ), are most often used in contexts outside of the organizational sciences. Interestingly, the formula used to derive Zeta is identical to formula for the $a_{WG}$ used in the organization sciences.

Differences between the two studies can also be noted. One distinguishing difference between the two different sets of studies is that all organizational science studies take place in groups (where individuals are the nested data points and the level of analysis is the group) and the studies reported in Table 2 take place at the level of the individual (where repeated measures are nested within the individual). This distinguishing point is expected to be of little methodological consequence, however, due to the fact that the research designs and statistics used to reflect the dispersion model construct are identical between the two contexts. Although there is some overlap, there are differences in the number of aggregated observations. Table 1 shows that the number of aggregated observations (i.e., groups) ranges from 9 to approximately 200. Table 2 shows that the number of aggregated observations (i.e., individuals) can range from 35 to approximately 20,000. Certainly as the number of observations increases within the study, the power will increase. But because Table 2 reports numerous studies that find support for the dispersion construct in observation ranges similar to those in Table 1, this difference is not likely to be a source of the discrepancies. The last difference between the two sets of studies is the type of variable commonly used. Studies which take place in the organization sciences use discrete interval type variables (also referred to as Likert-scaled variables) that result in discrete interval distributions. These measures are characterized by a bounded fixed number of discrete points (commonly 5 or 7 points), that are assumed to have an underlying continuum. Using these measures, a nested data point is obtained when an individual selects one of the ordered discrete points on the perceptual rating scale. In contrast, the studies listed in Table 2 are all derived from variables from continuous type distributions. For comparison purposes, a continuous type distribution may be unbounded or theoretically and/or practically bounded on one or more of the end-points, but the probability of reaching the extreme score is rare due to: 1) extreme outcomes associated with observations at the endpoints (e.g., a zero heart-rate, or an extremely high blood-pressure); or 2) because the range of potential scores is so great (e.g., 1 - 100 or 1 - 1,500, etc.) that the statistical properties of the resulting distribution is markedly different from a polytomous type.

Based on this review and comparison, it is suspected that the type of variable (i.e., discrete interval vs. continuous) is source of methodological discrepancies between the two contexts. In discrete interval distributions, the mean and variance are dependent. Thus, in dispersion prediction multiple regression models where both the average score and the dispersion index are included as predictors, there is an increased probability that this correlation can disrupt the model's performance. Second, theoretical and empirical dispersion prediction model research in a polytomous item context suggests that the relationship between the distribution's variance and a group level outcome may be non-linear. If a nonlinear relationship is overlooked during the analysis, and a linear model is executed, the results of the derived effect will be underestimated.

## 2.2 THE MEAN X VARIANCE CORRELATION AND THE MULTIPLE REGRESSION ASSUMPTIONS OF LINEARITY

### 2.2.1 The mean x variance correlation in discrete interval dispersion prediction models

As noted dispersion prediction model studies in the organizational sciences typically measure a facet of group climate. Prior to aggregation, measurement of the group-level construct is done at the individual level on a perceptual response scale typically comprised of 5 or 7 categories or points. Once all individual scores are collected, the resulting distribution of scores can be considered a discrete interval distribution which falls between a dichotomous and continuous distribution in terms of its mean x variance relationship.

In a dichotomous distribution the variance is determined by the mean as shown below:

$\mu_X = p$, where $p$ is the proportion of selections for the value of 1;

$\sigma_X^2 = \mu_X(1 - \mu_X)$.

Using this set of equations, the maximum variance is derived when the scores are distributed equally across 0 and 1. In this circumstance the mean of the distribution is .50 and its variance is equal to .25. As the distribution of scores has a higher proportion in the 0 or 1 category, the variance of the distribution will decrease. In other words as the mean approaches 0 or 1 the variance decreases.

Discrete interval distributions, derived from a polytomous item, display similar but slightly different rules that govern the relationship between the mean and the variance. Provided below are the formulas that Lindell and Brandt (2000) derived in order to express the relationship between the mean and variance in a discrete interval distribution:

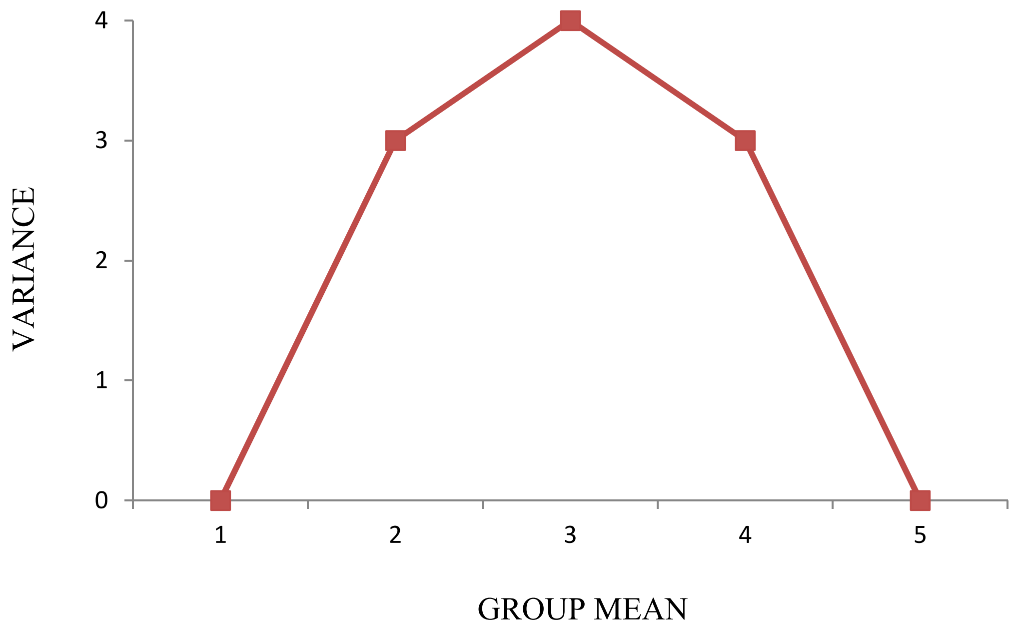
$\mu_X = \sum p_i X_i$, where $p_i$ is the proportion of scores that select the scale point $X_i$;

$\sigma_X^2 = \sum(p_i X_i^2) - {\mu_X}^2$.

Because there are numerous combinations of $\sum p_i X_i$ that can result in the same mean score, the exact value of $\sigma_X^2$ for any given mean is not precisely known.

Thus, a set of loosely structured general rules govern the mean x variance relationship for a given within-group structure in the discrete interval distribution. Figure 1 depicts this mean x variance relationship possibilities within a 5-point discrete interval distribution. The line in Figure 1 represents that maximum value of $\sigma_X^2$ for any given value of the mean with the area under the line representing the possible values for $\sigma_X^2$. In this 5 point, discrete interval distribution, therefore, there are numerous values of $\sigma_X^2$ that can exist for a mean value of 2; however, its absolute maximum value is 3. Figure 1 depicts that the maximum possible value for a given discrete interval distribution is at its midpoint. Figure 1 also suggests that, as the mean value reaches the extremes, the possible values for $\sigma_X^2$ decreases. When the mean of the within-group discrete interval distribution is at the extreme end-point (e.g., $\mu_X$ = 1), the only possible value for $\sigma_X^2$ is 0 (e.g., all nested data points were a 1).

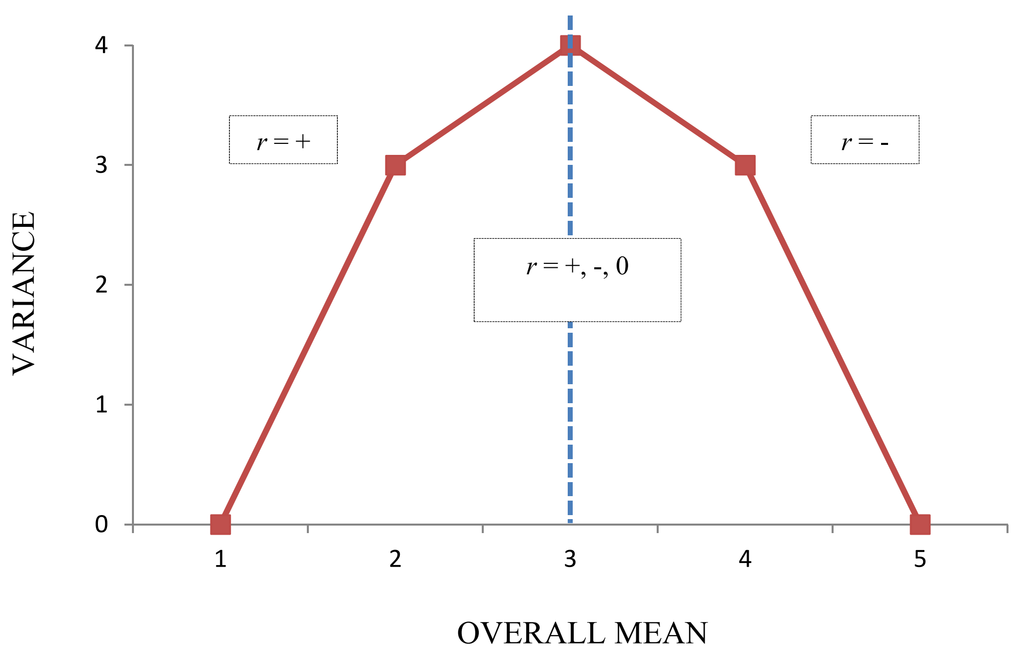
Figure 1: Within-group mean X variance relationship in discrete interval distributions




The preceding discussion suggests that there is a general dependence between the mean and variance in a within-group, discrete interval distribution. In dispersion prediction models, however, the level of analysis is at the aggregated level. As such a single observation is the aggregated group (or individual score in the case of a repeated measures design). Dependence among the nested data-point's mean and variance can manifest differentially depending on the mean x variance dependence patterns among the aggregated observations.

Figure 2 depicts the possible patterns of mean x variance correlations that can exist between-groups, across aggregated data points given the within-group mean x variance relationship. Figure 2 shows that the correlation between the mean and variance in the overall dataset depends on the location of the mean computed across groups. If, in the aggregated dataset the mean across groups is in the range above the scale's mid-point then the left half of the curvilinear relationship disappears for the most part, and the mean x variance correlation coefficient will most likely be negative. Conversely, an overall average score in the area below the midpoint will most likely result in a positive correlation due to the loss of aggregated observations that exist on the right, downward curve side of the chart. In the case where the overall mean is equal to 3, the correlation can be positive, negative, or zero depending on the pattern of mean / variance relationships that exist around the mid-point.

Figure 2: Mean X variance correlations based on overall mean of aggregated observations




Thus, there is likely to be a correlation between the mean and variance in the aggregated dataset in contexts where bounded, discrete interval type variables are used. This correlation may result in a strong correlation between the mean and the measure chosen to represent the dispersion construct. This suggestion is confirmed based on a review of the organizational science literature presented in Table 1 *above*. The far right column shows the correlations between the mean and dispersion index range from strong negative to strong positive. Only one study reported a mean x variance correlation close to zero (i.e., Moliner et al, 2005).

Although the direction of the relationship is most likely of little consequence, the magnitude of the correlation between the mean and variance might be. As is typical in dispersion model research (Cole et al., 2011), when controlling for the prediction of the outcome by the mean, significant correlations between the mean and variance could be the cause of small, statistically insignificant incremental effects of the dispersion construct and, if the correlation is high enough, this issues has the potential to violate the assumption of multicollinearity of the dispersion prediction multiple regression model. Properly specified multiple regression models assume that the predictors are not strongly correlated. Where two predictors do share a strong statistical relationship the regression coefficients can become unstable and biased in terms of their magnitude (Lomax, 2007; Pedhazur, 1997; Wilcox, 2003). High correlations between predictors can also inflate the standard error of the coefficients making it more difficult to detect significance (Lomax, 2007; Pedhazur, 1997; Wilcox, 2003).

To further complicate this issue, in discrete interval distributions there is an increased probability of the resulting distribution to be skewed. First, discrete interval distributions are bounded on both sides thereby creating a floor and ceiling effect. Second, discrete interval type variables typically require that an individual provide perceptual ratings of a stimulus (e.g., organizational or classroom environments). Due to the pervasiveness of cognitive and affective biases, theory and research suggest that distributions commonly encountered in organizational research tend to vary greatly in shape. Although non-normal skewed distributions can exist in any academic context (Micceri, 1989), researchers and theorists suggest that nested observations assessed through perceptual evaluations of individuals are often consistent due to social influence processes (where individuals are nested within groups) and/or biased because of psychological leniency or severity (Fisicaro & Vance, 1994; Funder, 1987; James, Demaree, & Wolf, 1984; LeBreton & Senter, 2008; Micceri, 1989; Schriesheim et al., 2001)

Skewed distributions may decrease the performance of dispersion prediction models in discrete interval distributions in several distinct ways: 1) the performance of dispersion indexes may not be robust to adequately deal with skewed distributions; or 2) the reliability (and even interpretability) of many of the indexes that can be used to reflect the dispersion construct breaks down as the mean reaches the lower or upper bounds of a distribution of scores (as in skewed distributions operating within discrete interval distributions); and, of primary interest in the current study, 3) because of attrition of the upper or lower half of the response scale in a skewed discrete interval distribution at least a moderate correlation between the distribution mean and dispersion is nearly certain. Although evidence suggests that distributional skew can influence measures of dispersion in each of the three ways mentioned, it is suspected that its primary impact on dispersion prediction models in discrete interval distributions is through an increased probability of correlation in the multiple regression model. Each of these issues is briefly discussed below.

*Robust estimation of scale and dispersion prediction models*. Although conducted prior to the development of most available dispersion indexes[3], simulation work designed to assess the performance of dispersion indexes in skewed distributions (i.e., Gross, 1976; Lax, 1975 and 1985; Tukey, 1960) suggests that dispersion indexes can be more or less susceptible to performance difficulties in these conditions. Tukey (1960) conducted simulations to explore the potential effect of distribution shape on the performance of dispersion statistics and noted that the standard deviation is affected by situations of even slight distributional non-normality. Because of the influence that slight deviations from normality have on the performance of the standard deviation, Tukey (1960) suggested that it represents a non-robust estimator of scale.

Other studies have come to a similar conclusion. While exploring the robustness of confidence interval estimates around a distribution's location parameter, Gross (1976) found that the standard deviation, "is by far the least efficient estimator" in contexts where the distribution departs from normal (p. 414). Gross (1976) also reports that confidence intervals around the location parameter derived from a median based dispersion statistic were robust across normal as well as non-normal distributions. Gross (1976) suggested that the median based estimates performed as adequately as heavily trimmed mean based confidence interval estimations probably "due to its more resistant scale estimator" (p. 413). Lax (1985) arrived at similar conclusions. While exploring the robustness of dispersion statistics across non-normal distributions, Lax (1985) found that, although the standard deviation performed near perfect across normal distributions, it performed "quite poorly" in distributions that departed from

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[3] The development of the $r_{WG}$ statistic took place around 1984 with the work done by James, Demaree, & Wolf (1984); $a_{WG}$ around 2005 with the work done by Brown and Hauenstien (2005); and the AD indices around 1999 with the work done by Burke, Finkelstin, & Dusig (1999). Research exploring the potential interaction between distribution shape and agreement / dispersion statistics took place prior to the mid-1980s.

normality (p. 740). Further, Lax (1985) found that the median based estimator of dispersion performed adequately in heavy-tailed distributions that departed from normality. Although dated and not inclusive of the majority of the statistics discussed throughout this paper, this simulation work suggests that an interaction between dispersion statistic performance and the shape of the distribution does exist.

The potential for skewed non-normal distributions to disrupt the performance of dispersion prediction models hinges on how well a potential index actually measures the objective dispersion among a set of scores. In other words, if a given dispersion index does not accurately measure the degree of underlying dispersion because of its poor performance in skewed distributions, any derived effect using this dispersion index in a dispersion prediction model can be questioned. There is some difficulty, however, in concretely suggesting that given dispersion index does not accurate reflect the dispersion present in a given distribution of scores. If a dispersion index systematically increases as the objective amount of dispersion within a set of scores increases, than an argument for measurement validity is reasonable.

*Dispersion index performance as the mean nears the distribution's end points*. In addition, dispersion index formulas and discussions related to their performance suggest that their estimation can become less reliable in bounded distributions as the mean score approaches the end points. Nearly all available statistics to measure within group / individual dispersion have performance issues in situations where the mean of a distribution is near the lower or upper bounds of the distribution. As will be discussed, the statistical properties of some of the most prominently used dispersion indexes across academic contexts (i.e., the *SD*, the *CV*, and the $a_{WG}$ / Zeta) suggest that estimates become unstable as the mean approaches the end-points; and in the case of the $a_{WG}$ / Zeta these estimates can become uninterpretable and meaningless. Although this issue can become problematic for dispersion prediction models in discrete interval distributions, it is not necessarily a systematic concern. In other words, this issue may be of concern for only the awg/Zeta and in heavily skewed distributions.

*Skew and mean* x *variance correlation*. In contrast to the two previously presented issues, a skewed discrete interval distribution almost certainly guarantees a moderate correlation between the distribution mean and variance. As reflected in Figure 2, if, in the aggregated dataset the mean across groups is in the range above the scale's mid-point (as in a negatively skewed distribution) then the mean x variance correlation coefficient will most likely be negative. Conversely, an overall average in the area below the midpoint will most likely result in a positive correlation due to the loss of aggregated observations that exist in the upper points of the scale. Based on a review of the organizational science dispersion model literature presented in Table 1, nearly all studies report a positive or negative mean x variance correlation. The prevalence of moderate mean x variance correlations suggest, in part, that skewed distributions are common in discrete interval distributions and therefore a significant, systematic concern for polytomous dispersion prediction multiple regression models.

### 2.2.2 Non-linearity dispersion prediction models in a polytomous item context

An important assumption of multiple regression is that both the predictor and outcome are linearly related. If this assumption is violated, and a linear regression is performed, the strength of the relationship between the two will be underestimated. Interestingly, evidence derived from existing empirical research suggests that dispersion prediction models in discrete interval distributions may be prone to a non-linear relationship. Several researchers have noted that a curvilinear relationship between the dispersion measure and the outcome may be a particular concern in dispersion prediction models (Cole et al., 2011; Dineen, Noe, Shaw, Duffy, & Wiethoff, 2007; Lindell & Brandt, 2000; Van der Vegt & Bunderson, 2005).

Lindell and Brandt (2000) were the first to identify the potential for a non-linear relationship to exist between the dispersion index and a group level outcome. In general, their arguments suggest that if the group mean and group outcome are linearly related, and the group mean and group dispersion are non-linearly related, there is likely a nonlinear relationship between the group dispersion and the group level outcome. Lindell and Brandt (2000) further suggested that because the mean and dispersion of a discrete interval distribution are dependent, both may take on nonlinear relationships with an outcome in a multiple regression model.

In 2007, Dineen et al. tested Lindell and Brandt's (2000) assertion that the group's variance may share a non-linear relationship with the group level outcome. In their 2007 publication they conducted two studies and tested Lindell and Brandt's (2000) logic through a polynomial regression using a quadratic term. Interestingly, using the standard deviation, they found that in one of their samples the quadratic terms for both the mean and the dispersion construct was not significant, but in the other sample the quadratic term for both the mean and the dispersion construct were significant. The correlation between the mean and dispersion construct for the first study was -.55 and for the second study, -.60.

If indeed, nonlinearity between the dispersion construct and a group level outcome is a problem for dispersion prediction models in discrete interval distributions, then there are two approaches to correct for this issue. The first method is to transform either one or both the predictor and outcome to achieve linearity, thereby allowing unbiased interpretations of coefficients derived from a linear regression model. One disadvantage of this approach is that results of the coefficients derived from the linear regression model need to be interpreted in terms of the transformed rather than the original variables (Lomax, 2007; Wilcox, 2003). The second method entails using a nonlinear regression technique such as polynomial regression, which has the advantage of preserving the variable(s) in their original scale (Lomax, 2007; Wilcox, 2003). Non-linear regression models have some appeal for dispersion prediction models in that researchers are able to preserve the unique theoretical appeal of each of the dispersion measures chosen (Cole et al., 2011).

Although there is theory and speculation that a systematic concern of non-linearity in polytomously derived dispersion prediction models may be an issue, questions as to the severity of its impact remain. Given the increased probability that this multiple regression assumption may be violated in dispersion prediction models, these research questions are worthy of exploration.

## 2.3 A REVIEW OF THE DISPERSION MEASURES USED IN DISPERSION PREDICTION MODELS: ADVANTAGES AND DISADVANTAGES

The arguments presented thus far suggest that the two possible systematic influences on the performance of dispersion prediction models in discrete interval distributions are: 1) an increased likelihood that the distributions mean and the distribution dispersion are dependent; and, 2) an increased likelihood of violating the regression assumption of linearity. Cole et al., (2011) suggested that, depending on the research question involved and the dispersion model in question, the index used to reflect the dispersion construct should be carefully chosen. To date, however, little substantive guidance is available as why some dispersion indexes may be preferred over others. In lieu of the possible influences of poor dispersion model performance in discrete interval distributions, it is possible to review the potential advantages and disadvantages of the dispersion indexes available.

Most dispersion prediction models across academic disciplines use the sample standard deviation (*SD*) or the coefficient of variation (*CV*). There are, however, numerous statistics that can be used to reflect the dispersion construct in dispersion prediction models. Each has a different formula and prospective statistical properties. Table 3 presents formulas for each of the single item and multi-item within-group agreement and dispersion statistics. In the following section, each of the indices presented in Table 3 (*SD*, *CV*, $r_{WG}$, $a_{WG}$, $AD_M$, $AD_{Md}$, *MAD*) will be discussed in terms of its potential to minimize dependence on the mean and, therefore, the potential for nonlinearity in dispersion prediction multiple regression model.

Table 3: Dispersion Model Indexes

| | Single Item Formulas | Multiple Item Formulas |
|---|---|---|
| $r_{WG}$ | $1-(\frac{s^2}{\sigma^2})$<br>$s^2$ = observed variance<br>$\sigma^2$= expected variance (based on a chosen null distribution) | $\frac{J\,[1-\left(\frac{s^2}{\sigma^2}\right)]}{J\left[1-\left(\frac{s^2}{\sigma^2}\right)\right]+(\frac{s^2}{\sigma^2})}$<br>$J$ = the number of items<br>$s^2$ = observed variance<br>$\sigma^2$= expected variance (based on a chosen null distribution) |
| $a_{WG}$ | $1-\frac{2s^2}{s^2_{\bar{X}pv\mid\bar{X}}}$<br>$s^2_{mpv\mid m}=[(H+L)\bar{X}-\bar{X}^2-HL][K/(K-1)]$<br>$s^2$ = observed variance<br>$\bar{X}$ = group mean<br>$H$ = is the maximum possible value of a scale<br>$L$ = is the minimum possible value of the scale.<br>$K$= group size | $\frac{\sum_{j=1}^{J}a_{WG(J)}}{J}$<br>$J$ = the number of items |
| $AD_M$ | $\frac{\sum_{i=1}^{N}\lvert X_{jk}-\bar{X}_j\rvert}{N}$<br>$N$ = number of judges or observations for an item (i.e. the total number of deviations for an item)<br>$X_{jk}$ =kth judge's score on item j<br>$\bar{X}$ = group mean of the judges scores on item j | $\frac{\sum_{j=1}^{J}AD_{M(J)}}{J}$<br>$J$ = the number of items |
| $AD_{Md}$ | $\frac{\sum_{i=1}^{N}\lvert X_{jk}-Md\rvert}{N}$ | $\frac{\sum_{j=1}^{J}AD_{Md(J)}}{J}$ |

| | | |
|---|---|---|
| | $N$ = number of judges or observations for an item (i.e. the total number of deviations for an item)<br>$X_{jk}$ =kth judge's score on item j<br>$Md$ = group median | $J$ = the number of items |
| SD | $$SD = \sqrt{\sum_{k=1}^{K} \frac{(X_i - \bar{X})^2}{k-1}}$$<br>$X_i$ = individual observations<br>$\bar{X}$ = group mean<br>$K$ = group size | |
| CV | $$CV = \frac{SD}{\bar{x}}$$<br>$SD$ = group standard deviation<br>$\bar{X}$ = group mean | |
| MAD | $$MAD = med\{\lvert x_i - Md \rvert\}$$<br>$med$ = median<br>$x_i$ = individual observations<br>$Md$ = group median | |

### 2.3.1 Standard Deviation

Based on a review of the literature, the standard deviation (*SD*) is the most often used dispersion index across all disciplines represented in the sample of studies shown in Tables 1 and 2. As apparent from Table 1 *above*, over half of the located dispersion model studies (~56%) use the sample *SD* as the statistic of choice when testing hypotheses related to a theoretically operationalized dispersion model of emergence. Table 2 suggests that nearly 100% of the studies conducted outside of the organizational sciences use the index. The popularity of the *SD* for use in dispersion models is most likely due to the simple logic voiced by Schneider, Salvaggio, and Subirats (2002) in which they suggested that "most people think about variability in terms of the standard deviation" (p. 223). Based on their simulation conducted within the context of a discrete interval variable, Roberson et al (2007) recommended the use of the *SD* for dispersion prediction models. Roberson et al's (2007) general endorsement of the *SD* suggests that its choice as the most popular statistic to represent dispersion models in the organizational sciences will continue.

The statistical properties of the *SD*, however, suggest that it may not measure up well in terms of the potential issues related to dispersion prediction model performance in discrete interval distributions. As a variance based estimate of dispersion, the *SD* is subject to the mean x variance relationship depicted in Figure 1. In other words, the sample mean and sample *SD* will display the same type of mean x variance relationship and correlation patterns displayed in Figure 1 and Figure **2**. Therefore, in terms of its ability to minimize the potential for mean x index dependence and nonlinearity with the mean within dispersion prediction models, it may not measure up well. Further, consistent with the results of studies conducted by Gross (1976), Lax (1975; 1985), and Tukey (1960) presented above, slight deviations from normality can influence the SDs performance. It also may exhibit performance issues as the mean approaches the distribution end-points. These issues, however, are less likely to impede its performance within dispersion prediction models when compared to the *CV* and the $a_{WG}$ / *Zeta*.

### 2.3.2 Coefficient of Variation

The coefficient of variation (*CV*) is also commonly used to reflect the dispersion construct in dispersion models. Based on a comparison of Tables 1 and 2, the *CV* is used more often outside of the discrete interval distribution context.

The *CV* is calculated simply by dividing a sample's standard deviation by its mean. In this way it is essentially an estimate of group differences in comparison to the mean (Bedeian & Mossholder, 2000). The performance of the *CV* is expected to be different between polytomous and continuous distribution contexts. Where a continuous variable is not bounded, the *CV* and mean will have no relationship. In a continuous type variable that is bounded, the *CV* will increase when the mean score is at the lower bound (as a small *SD* is divided by a small mean) and decrease as it approaches the upper extreme score (as a small *SD* is divided by a large mean). In a discrete interval distribution the relationship is expected to be somewhat linearly negative and increase quickly at the lower bound and drop off quickly at the upper bound. Thus, although the mean x *CV* relationship is distinct from the mean x variance & the mean x *SD* relationship, there is still a relationship. Therefore, the CV does not necessarily measure up well in terms of its ability to minimize the potential collinearity with the mean, especially in discrete interval variable contexts.

The *CV*'s potential performance across skewed distributions is not promising. First, because it incorporates the *SD* into its numerator and the mean in the denominator its robustness may be less than optimal in skewed distributions. Further, the mean x *CV* relationship suggests as the mean approaches the end points the *CV* becomes less stable. In contrast to *CV* estimates when the mean is in middle of a bounded distribution, as the mean approaches the end-points, very small changes in the mean result in large changes in the *CV*. Finally, the *CV* is negatively related to the mean in a discrete interval distribution. When the mean is near the lower end of the response scale (as in a positively skewed distribution) the value of the *CV* will be largest. Conversely, when the mean is near the upper end of the response scale (as in a negatively skewed distribution) the value of the *CV* will be smallest. When the mean is near the response scale midpoint, the value of the *CV* can fluctuate depending on the degree of dispersion among the nested data points. Thus, very different values for the *CV* can be derived for the same objective variance with different mean values. This type of statistical behavior suggests the possibility for erratic and non-systematic performance of the statistic in bounded, non-normally skewed distributions. This may be especially true when analysis is done on an aggregated data set in which distributions of the aggregated data points vary between positive and negative skew. For these reasons, it is suspected that the performance of the *CV* may be less than optimal for use in polytomous items.

### 2.3.3 $r_{WG}$

Both the single item and multiple item interrater agreement indices ($r_{WG}$ and $r_{WG(J)}$, respectively) were proposed as useful statistics to quantify the level of agreement among multiple judges, on an ordinal/rating scale type outcome, in a ratio which reflects the degree of reduction in error variance (James, Demaree, & Wolf, 1984). Although it is rarely used in dispersion prediction models in the organizational sciences, LeBreton & Senter (2008) argue that the $r_{WG}$ is perhaps the most popular agreement statistic; its use ranging across multiple disciplines.

The $r_{WG}$ is essentially one minus a ratio of the observed variance (x) to the 'expected' or 'null' variance (y) (i.e., 1 – x/y), where the 'expected' or 'null' variance (y) can have many meanings. Consistent with classical test theory, $r_{WG}$ indices assume that rater variability around a single unobserved true score can be considered error variance (LeBreton & Senter, 2008). Where the variance among various raters on the target is zero (0), $r_{WG}$ will be equal to one (1), representing perfect agreement. As the variance among the raters increases in relation to the null or expected variance, $r_{WG}$ approaches zero (0).

Distinct from measures of inter-rater reliability (e.g., ICC1 and ICC2), $r_{WG}$ does not include a between group variance component and, therefore, is useful when a restricted number of groups is limited. Thus, even in one group empirical research contexts the $r_{WG}$ statistic can be useful and informative. However, when large numbers of groups are considered, the use of $r_{WG}$ becomes more complex because the statistic must be computed individually for each group (LeBreton & Senter, 2008).

When used to justify aggregation of consensus and referent shift aggregation models, the choice of the null distribution is the most significant issue related to its use (Cohen, Doveh, &

Eick, 2001; LeBreton & Senter, 2008). The traditional .70 cutoff value which justifies aggregation based on a distributions average score can be more or less easily obtained using a different value for the expected variance in the denominator. As the variance used in the denominator increases the $r_{WG}$ value also increases. Thus, increasing the null variance in the denominator can be done in order to obtain and or exceed the required cutoff value.

The most common null distribution used in organizational science research using the $r_{WG}$ is the uniform distribution. For the purposes of dispersion prediction models, where the concern is rank ordering of the level of dispersion and using it to predict outcomes, the choice as to which null distribution to use has little bearing on the derived regression coefficient and effect size; as argued, the key is a consistent systematic rank ordering across different distributional shapes and its independence from the mean. Thus, a null variance based on a uniform, maximum, or expected variance for a given shape can be used.

Given this line of reasoning, the $r_{WG}$ seems to have performance patterns very similar to that of the *SD*. The $r_{WG}$ will most likely share a relationship with the mean similar to the relationship that the mean shares with the *SD*. Because the ratio of the observed to expected variance is subtracted from one, however, the relationship between the $r_{WG}$ and the mean will be inverted. In other words, where the mean approaches extreme scores on a bounded distribution, the value for the $r_{WG}$ will most likely be maximum (expressing maximum agreement). Conversely, where the mean is near the distribution's midpoint, the $r_{WG}$ is most likely to be minimum. Therefore, the pattern of correlations between the $r_{WG}$ and the mean will be reversed when considering the location of the overall mean across aggregated observations; however there is still a pattern and, thus, a resulting dependence between the mean and this measure of dispersion.

### 2.3.4 $a_{WG}$ index and Zeta

Brown & Hauenstein (2005) developed the $a_{WG}$ indices due to limitations they noted with the $r_{WG}$ indices. The authors took specific issue with $r_{WG}$ because of its scale dependence and the potential bias that can result from the improper choice of the null distribution variance. To that end, Brown & Hauenstien (2005) extended the logic of Cohen's kappa to a single target situation with the $a_{WG}$ indices. $a_{WG}$ is consistent with $r_{WG}$ but it replaces the variance of the null distribution with a formula that frees it from problems associated with the distribution choice and scale dependency by integrating the scale points and the mean into the denominator. By incorporating the possible response range and mean within the denominator of the formula for the index, the authors are able reflect the dependence between the mean of a set of responses and its potential variance.[4] Although referred to as a distinct statistic in cognitive and performance assessment disciplines (i.e., Zeta [ζ] by Golay, Fagot, & Lecerf, 2013), the statistical properties of the $a_{WG}$ (and or Zeta) make it an attractive dispersion predictor model statistic.

Because it is subtracted from 1, similar to the $r_{WG}$ index, a relationship with the mean may be expected to be a 'U' shape with the maximum agreement score at the end points of the distribution. However, because the *denominator* adjusts for the mean and scale and decreases in magnitude as the mean approaches the scales end-points (and is not fixed as with the $r_{WG}$ index),

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[4] By incorporating the upper and lower bound of the scale into the index's formula, the $a_{WG}$ requires that the lower and upper scale points of the distribution are known.

the $a_{WG}$ index frees itself from some of the statistical dependence that the variance and *SD* share with the mean. Brown & Hauenstein (2005) note that the adjusted denominator is actually the maximum possible variance that a mean value can display for a given range of scores. In this sense, the $a_{WG}$ index seems to be a possible recommendation for use in dispersion prediction models.

However, one notable limitation of the $a_{WG}$ index results from its performance as the mean approaches the distribution end-points. In these instances the value of $a_{WG}$ (or Zeta-Golay et al. 2013) becomes much less reliable. As Brown & Hauenstien (2005) point out, one limitation to the statistic is that when the mean approaches the extremes of the scale (as in a skewed discrete interval distribution), $a_{WG}$ is not able to produce values that have consistent interpretability. They illustrate the issue through an example in which 10 observations are obtained for a 5 point scale and the generated mean is 1.3. In this scenario, it would not be possible for any of the 10 raters to have selected a 5. Thus, in situations where there is a small number of raters and collectively their distribution has a mean near one of the extreme scores calculating agreement using the $a_{WG}$ index may produce values outside of the -1 to + 1 range or result in a division by zero and loose its interpretability (Brown & Hauenstien, 2005)[5]. As a result, Brown & Hauenstien (2005) and Golay et al. (2013) argue that researchers should be cautious when $a_{WG}$ / Zeta statistics to compute agreement in situations where the mean nears the scale endpoints and the group size is small.

[5] Equations (7) and (8) from Brown & Hauenstien, (2005) produce the minimum and maximum mean that can produce accurate $a_{WG}$ indices given the scale range and number of raters. Minimum mean for accurate $a_{WG} = \frac{L(k-1)+H}{k}$; Maximum mean for accurate $a_{WG} = \frac{H(k-1)+L}{k}$. Where *H* equals the maximum scale value, *L* is the minimum value, and *k* is the number of raters in the group.

### 2.3.5 Average Deviation Indexes

Similar to the $r_{WG}$ and $a_{WG}$ indices, Burke, Finkelstin, & Dusig (1999) created the *AD* indices as a measure of agreement for scale rating multiple observations of a scaled measurement device. The *AD* statistics are essentially calculated as the average of the absolute differences between each observation and the chosen measure of central tendency (Burke et al, 1999). Burke et al (1999) argues that the primary benefit of the *AD* over the $r_{WG}$ and $a_{WG}$ indices, is that the *AD* indices estimates agreement in the metric of the original scale and unlike the $r_{WG}$ statistic is that it does not require the use of an assumed null distribution variance.

The *AD* index can be estimated around the mean ($AD_M$) or the median ($AD_{Md}$). In a study conducted by Burke et al (1999) the authors found $AD_M$ and $AD_{Md}$ to be highly correlated with each other and the *SD* and negatively correlated with the $r_{WG}$ index. Interestingly, however, the authors did note differences in performance between the $AD_M$ and $AD_{Md}$. They found that the $AD_{Md}$ most accurately captured the a priori specified range of agreement across a set of simulated distributions leading them to conclude that "the $AD_{Md}$ index is thus more sensitive in terms of detecting interrater agreement in comparison to $AD_M$" (p. 63).

In contrast to $r_{WG}$ and $a_{WG}$ indices, and similar to the *SD*, smaller values of the *AD* indices reflect higher agreement among the raters, thus some suggest that, similar to the standard deviation, it may be better termed a measure of disagreement rather than agreement (Burke & Dunlap, 2002). Computationally, it also shares similarities with the standard deviation and thus it is expected to display a relationship with the mean similar to that of the *SD*. Burke & Dunlap

(2002) argue that its primary benefit is that “the *AD* index allows researchers to more directly understand (intuit) what disagreement is in terms of the original measurement scale” (p. 168). Further, because the *AD* indices provide a median based method to compute the statistic, it has been argued to have the potential to provide unbiased estimates of agreement in the presence of non-normality and outliers (Burke & Dunlop, 2002; Burke et al, 1999; LeBreton & Senter, 2008; Newman & Sin, 2009).

### 2.3.6 Median Absolute Deviation

Conceptually the median absolute deviation *MAD* is the middle of the distribution of deviations from the median of the observations. The *MAD* has been found to be relatively robust when compared to the standard deviations in distributions that depart from normality. Of all of the dispersion indexes discussed thus far, the *MAD* seems the most robust measure of dispersion (Hoaglin, Mosteller, & Tukey, 1983). As this measure is based on deviations from the median, in skewed distributions there is also decreased potential for this measure to be correlated with the mean as well as experience substandard performance issues when the mean is near the end-points of the scale.

### 2.3.7 Summarizing the theoretical strengths and weaknesses of dispersion indexes for use in dispersion prediction models

Figure 3 was developed based on the discussion presented thus far related to the theoretical correlation between each of the dispersion statistics and the mean. Figure 3 shows the theoretical correlation of a distribution's mean with the *SD*, $r_{WG}$, $a_{WG}$, $AD_M$, and the *CV* in a hypothetical discrete interval distribution. The $AD_{Md}$ and the *MAD* are both omitted from the chart due to uncertainty as to the relationship between the mean and these dispersion indexes.

Figure 3: Summary of the statistical relationship with the mean for the *SD*, $r_{WG}$, $a_{WG}$, $AD_M$ indexes, and the *CV*

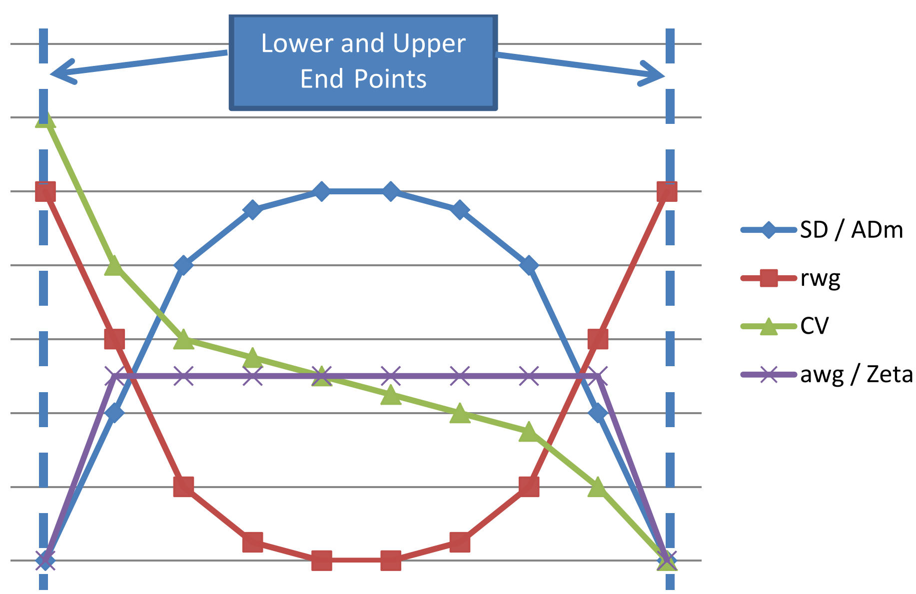



Figure 3 shows that measure can be more or less correlated with the mean and that the $a_{WG}$ / Zeta is, perhaps, the least correlated. Figure 3 also shows that each of the dispersion indexes seemingly have performance difficulties as the mean approaches the lower and upper end-points of the distribution. Although the $AD_{Md}$ and the *MAD* are not included in the chart, as the mean approaches the end-points of the distribution their performance is suspected to be relatively stable given their median based estimation.

### 2.3.8 Median based level covariate

It is common practice within dispersion prediction model empirical studies to control for the mean of the distribution in the regression equation (Cole et al., 2011; Bliese & Halverson, 1998). Cole et al., (2011) articulate the rationale behind using the mean as a covariate in the following quote:

> …because of statistical dependence, absolute-level effects should be treated as a covariate when exploring the relationship between a dispersion variable and a criterion. It is impossible to determine the extent to which a dispersion variable is actually related to the study criteria being examined without establishing and controlling for the degree of interdependence between the level and dispersion components of a group-level predictor…[this is] crucial because failing to consider and control for absolute level effects leaves 'open the possibility that the observed variance effects are a spurious by-product of absolute level effects' (Bliese & Britt, 2001, p. 433) and, by extension, doubt as to whether a dispersion effect actually exists (p.723).

Although is it common practice to control for the mean of the distribution, it is suggested that controlling for the median in dispersion prediction models allows for the control of the level-effect but may increase the power of the dispersion index by reducing the correlation with the central tendency, level-effect covariate in the model. Similar to using a median-based formula for dispersion (i.e., the *MAD* and/or the *ADmd*) and controlling for the mean to reduce the correlation between the two covariates in the model, controlling for the median may reduce the correlation with mean-based estimators of dispersion (i.e., the *SD* and/or *ADm*).

# 3.0 METHODS

In order to explore whether or not the mean x dispersion correlation and nonlinearity influence the performance of dispersion prediction models in discrete interval distributions across the different dispersion indexes, Monte Carlo simulations were performed in the discrete interval context using a 5 point polytomous scale considering both normal and skewed distributions. The research questions are restated as follows:

1. Do the dispersion indexes present nonlinearity and / or heteroscedasticity in dispersion prediction multiple regression model in a polytomous item context?

2. To what extent does the correlation between the dispersion index and the level covariate in dispersion prediction multiple regression models impact their performance in a polytomous item context? More specifically, the questions are:
    - 2.1. Does the dispersion index computed from a skewed distribution affect the performance of the dispersion index in dispersion prediction model?
    - 2.2. Does the dispersion index computed from 5 polytomous items improve performance over those calculated from 1 polytomous item?

2.3. Does the use of median as the level covariate improve the performance of the dispersion index when compared to models that use the mean as the level covariate?

2.4. Is there difference among the dispersion index in their performance and is such difference dependent on the distribution shape, the number of items used to calculate the dispersion index, and the use of mean or median as the 'level' covariate?

## 3.1 SIMULATION STUDIES

In order to reflect the conditions common in discrete interval distribution dispersion prediction model studies, Monte Carlo studies were conducted in which the objective within distribution standard deviation was related to a hypothetical group outcome with a specified effect. The shape of the distribution of nested data points ranged from normal to varying degrees of skew. By simulating distributions with distinct levels of skew a wide range of potential mean x variance levels was expected. Once the nested data points were generated according to specifications, the dispersion statistics were calculated from the nested data points and, in turn, used to predict the generated group level outcome variable. Each of the statistics was then evaluated in terms of its correlation with the 'level' covariate (in terms of *VIF* of the dispersion index), the unique and comparative performance in explaining the variance of the outcome (in terms of $R^2$ for the full model, and $sr^2$ for the dispersion construct) and recovering the specified relationship between the dispersion construct and the outcome (power and Type I error rates). In addition, linearity of the relationship between the dispersion construct and the outcome and the homoscedasticity of the errors in the dispersion prediction model were examined.

### 3.1.1 Design of the simulations

Table 4 presents the independent variables and levels applicable to the simulations.

Table 4: Independent variables and levels

| Simulation Parameters and Levels | |
|---|---|
| Parameters | Levels |
| Number of Nested Data Points (NDP) | 15, 30, 100 |
| Number of Observations (Ob) | 30, 60, 120, 400 |
| Effect of group-level dispersion ($\beta_2$) | .00, .10, .30, .50 |
| Shape of distribution | Normal, Moderate Skew, Heavy Skew |
| Number of items from which the dispersion index is computed | 1, 5 |
| Dispersion Indexes | *SD, CV,* $a_{WG}$, *ADm,* $AD_{Md}$, *MAD* |
| Central Tendency Covariate in the Multiple Regression | *Mean, Median* |

In Table 4 the simulation variables and their associated levels are presented. As reflected in Table 4, and consistent with the values reported in Table 1 and Table **2**, the number of nested data points included the following levels: 15, 30, and 100. This range was expected to be applicable to group studies and within-person, longitudinal studies. Previous simulation work in the context of organizational sciences (i.e., Roberson et al, 2007) has included a maximum of 25 nested data points, however empirical explorations of the effect of the dispersion composition model has been conducted on groups with over 200 (e.g. Dawson, Gonzalez-Roma, Davis, & West 2008; Dickson, Resick, & Hanges, 2006). Although one of the assumptions of the dispersion model for group studies is that the construct be operationalized in a uni-modal, intact group, given the existing empirical work executed on groups that range from 3 to >200 individuals, it seems plausible that operationalizing the construct in groups with a large number of nested data points (i.e., 100 and 200) is realistic. Thus, the levels of the number of nested data points were varied to mirror the wide range of possible group sizes and repeated individual measures.

The number of aggregated observations was varied at the following levels: 30, 60, 120, and 400. These observations are a realistic number of aggregated observations encountered across academic disciplines where dispersion prediction models are of interest. In cases of repeated measures, longitudinal type studies, the maximum number of observations was nearly 20,000. This number far exceeds the number of groups seen in organizational science studies the number of observations that would logically be needed to detect a significant effect.

In order to explore the range of potential effect sizes (zero, small, medium, large), the effect of aggregated dispersion construct (β2) was varied from .00, .10, .30, and .50. The effect of the mean (β1) was held constant at .30.

The shape of the distribution was also set to vary: normal, moderate positive skew, and heavy positive skew. As discussed, by varying the shape of the distribution between normal and varying degrees of skew, the mean x variance correlation also varied.

Three other simulation factors were considered which were suspected to influence the level/strength correlation and, in turn, the performance of dispersion prediction models. First, the number of polytomous items used to compute the dispersion index was set to be one and five. In the one-item case, the nested data points were on a discrete interval scale with five possible values. In the five-item case, the nested data points were the average of responses for the five items thereby increasing the potential variability between the upper and lower discrete points. By increasing the potential variation between the upper and lower bounds of the discrete distribution properties similar to a continuous distribution are suspected. In the five item context, the correlation between the level and the strength was expected to decrease, and in-turn, hypothetically increase the performance of the dispersion prediction model. Second, mean-based dispersion indexes (e.g., *SD*, *ADm*) were supplemented with median-based dispersion indexes (e.g., *ADmd*, *MAD*), and third, the level covariate varied to include both the mean and median. Varying robust and non-robust estimates of scale and central tendency created a variety of dispersion index—central tendency covariate combinations used in the dispersion prediction multiple regression models. Through assessment of these models in skewed distributions it was expected that the best performing combinations of dispersion index/level covariate would be realized through the lowest correlations between the predictors.

### 3.1.2 Data generation and analysis algorithms

Table 5 reports the steps necessary to generate and analyze the data for five point discrete interval scaled variables from a normal distribution. Consistent with this previous simulation research (i.e. Bliese, 1998; Bliese & Halverson, 1998; Roberson et al, 2007) the current simulation used the total amount of individual variance explained by the group's mean as the objective representation of the group's dispersion. This technique involved generating a set of random numbers to represent the mean of each distribution, a-priori specifying the degree of dispersion around the generated mean, and integrating the mean and dispersion into a regression-based data generation equation.

Specifically, in step 1 the within-group variance ($\delta^2_D$) was generated from a uniform distribution for each group and within-group standard deviation was calculated. The next step in the algorithm required that each $\delta_D$ be standardized to ensure consistency among the coefficients entered in the regression equation used to generate the group-level outcome. In order to standardize the group's standard deviation the empirical mean and standard deviation of $\delta_D$ were obtained by calculating the mean and standard deviation of 10,000 values from a uniform distribution; .6677 and .2351 respectively. In Table 5, step 3 was used to generate the mean of the group-level construct in the standard normal form ($G_j$). Using the standard normal mean ($G_j$), the standardized group dispersion ($\delta'_D$), and each of the regression coefficients ($\beta_1$ and $\beta_2$) the group level outcome was generated using the regression equation specified in step 4. Step 5 entails using each group's within-group variance ($\delta^2_D$) and mean ($G_j$) to generate each of the individual level observations that comprise each distribution ($X_{ij}$).

In step 5, Roberson et al's (2007) equation was used to generate the individual level observations in a regression based data generation equation:

$$X_{ij} = \left[sqrt(1 - \delta_D^2) \times G_j\right] + \left[sqrt(\delta_D^2) \times N(0,1)\right] \qquad [1]$$

where, $\delta_D^2$ is the objective level dispersion of the distribution (i.e., within-group variance); and $G_j$ is the simulated group mean.

In step 6, the continuous individual level observations were rescaled to an ordinal variable with 5 categories. The rescaling method is discussed below.

In step 7 and 8, with the rescaled ordinal individual observations, the mean, the median, and dispersion/agreement indices for each group were computed. The dispersion/agreement indices used in the following simulation include *SD, ADm, ADmd, CV,* $a_{WG}$ and *MAD*. The rwg was omitted because of its hypothesized performance redundancy with the *SD* and *ADm*.

In step 9, correlations among the dispersion/agreement indices were recorded.

In step 10, the assumptions related to a linear regression model were then assessed, including linearity and homoscedasticity.

In step 11, the dispersion prediction models were fit by regressing the group outcome on the group mean and each of the dispersion indexes. The $R^2$, the $sr^2$, p-value of the partial t-test of the regression coefficients, and the *VIF* for the regression coefficients were then recorded.

In step 12, the dispersion prediction models were fit by regressing the group outcome on the group median and each of the dispersion indexes. The $R^2$, the $sr^2$, p-value of the partial t-test of the regression coefficients, and the *VIF* for the regression coefficients were then recorded.

The above steps were repeated for each simulation condition, and for each simulation condition 1000 iterations were performed.

Compared to Roberson et al.'s (2007) data generation steps, this data generation algorithm included a slightly different method to generate the group outcome variable. Roberson et al., (2007) used the within group variance as the measure of dispersion in the data generation model in step 4. Rather than the variance, the current study used the within-group standard deviation. Roberson et al., (2007) also included an interaction effect of medium effect size (standardized regression weight = .3) between mean and within-group variance (dispersion measure) and treated it as a covariate in the dispersion prediction model. Even though this interaction effect is sometimes included as a covariate in the literature when the moderating properties of the dispersion construct are of primary interest, the interaction effect was excluded in the current study as the focus was on the main effect of the dispersion index. If the interaction effect were included in the regression as an additional covariate, the first-order effect of the dispersion index would be interpreted as the effect of dispersion index when the group level covariate was zero. Such an interpretation would have placed more emphasis on the interaction effect than on the main effect of the dispersion index.

Table 5: Data generation and analysis algorithm for discrete interval scales variables

1. For each group, generate dispersion $\delta_D^2 \sim U(0,1)$. This will generate a different variance/SD for each group

2. Standardize $\delta_D$ to be $\delta'_D$

3. Generate the means for the distributions of individual level observations (G)
$$G \sim N(0,1)$$

4. Generate the outcome for each group outcome $\left[\beta_1 \times G_j + \beta_2 \times \delta'_D\right] + [sqrt(1-(\beta_1^2 + \beta_2^2)] \times N(0,1)$

5. Generate individual-level ratings ($X_{ij}$) that comprise each group (for non-normal data, N(0,1) is replaced by chi-square distribution)
$$X_{ij} = \left[sqrt(1-\delta_D^2) \times G_j\right] + [sqrt(\delta_D^2) \times N(0,1)]$$

6. Scale the individual-level rating to a 5 point scale. For one item case, use item 1 as the individual-level rating for further steps; for five item cases, calculate the mean of five items as the individual-level rating for further steps.

7. Calculate mean and median for each group

8. Calculate agreement / dispersion indices for each group, including SD, ADm, ADmd, awg, CV, and MAD

9. Run correlations among the dispersion / agreement indexes

10. Assess linearity, multicollinearity, and homoscedasticity of each dispersion/agreement index.

11. Run regression analysis
$$Group\ Outcome = B_0 + B_1\bar{x} + B_2 dispersion$$

12. Run regression analysis
$$Group\ Outcome = B_0 + B_1 Median(X) + B_2 dispersion$$

### 3.1.3 Operationalizing skewed distributions

One important issue in generating data corresponding to the moderate and heavy skewed shapes was to operationalize / quantify the meaning behind the qualitative descriptions of skew provided. Although LeBreton and Senter (2008) did not provide exact skewness statistics to numerically represent each of the three qualitative descriptions, the authors did provide the percentage of responses for each of the response options within various discrete interval response scales (5, 7, 9, and 11) for each of the three qualitative descriptions of slight skew, moderate skew, and heavy skew. In order to obtain a quantitative value of skew for each distribution shape multiple simulations were executed. For the simulations, data was generated in which the percentage of responses was specified for each response option in each of the scales according to the specifications provided by LeBreton and Senter (2008), and the skew of these distributions was then obtained. Because an accurate computation of skew required that at least one response was observed for each category it was necessary to provide a very small probability of response for categories in which LeBreton and Senter (2008) indicated a 0% probability of response. In these cases (i.e. the moderate and heavy skewed distributions) 0% probabilities were substituted with a .01% probability which was subtracted from the adjacent cell probabilities to ensure the sum of the resulting probabilities was unity. In order to obtain positive skewness values a severity bias was simulated in lieu of the leniency bias provided by LeBreton and Senter (2008). The skewness values obtained from simulating 1,000,000 observations are reported in Table 6.

Table 6: Skewness of Lebreton and Senter's (2008) skewed distributions

| | Proportion Endorsing Each Value (5-point scale) | | | | | |
|---|---|---|---|---|---|---|
| Response Option | 1 | 2 | 3 | 4 | 5 | Skew |
| 5-point scale | | | | | | |
| Slight Skew | .25 | .35 | .20 | .15 | .05 | .5369 |
| Moderate Skew | .35 | .40 | .15 | .09 | .01 | .8228 |
| Heavy Skew | .50 | .40 | .08 | .01 | .01 | 1.418 |

Based on these results, and for the purpose of this simulation, the following skew values are adopted for each of the skewed distribution qualitative descriptions: *Moderate Skew* is around .8; and *Heavy Skew* >1.40.

In the data generation regression equation [1] it can be observed that the error term is specified as normally distributed, N(0,1). Thus, it was expected that the distribution of the resulting individual observations would take on a normal shape. Theoretically, then, it was suspected that the distributional shape of the generated data might be controlled through different specifications of the error term while simultaneously specifying the group's dispersion. The $\chi^2$ distribution is one such distribution that has been used previously to achieve some level of skew in simulated data (e.g., Long & Ervin, 2000). Using the $\chi^2$ distribution a wide range of theoretical skew can be achieved by varying the degrees of freedom (skewness = $\sqrt{[8/df]}$); where $\chi^2(3)$ has a skew of 1.63 and $\chi^2(10)$ has a skew of .89.

In order to generate the skewed distributions, the probability density function for the $\chi^2$ distribution was incorporated into equation [1] above to yield the following equation [2] with degrees of freedom as 3 for heavy skew and 10 for moderate skew distributions.

$$X_{ij} = \left[sqrt(1 - \delta_D) \times G_j\right] + \left[sqrt(\delta_D) \times (\chi^2(df) - df)/sqrt(2 \times df))\right] \qquad [2]$$

Consistent with the simulated normal condition, the chi-square distribution was standardized first to ensure that the distribution of the individual scores was standardized with mean of zero and standard deviation of 1. It is also important to note that in Step 4 when the group outcomes were calculated for the normal distributions, the mean and standard deviation are independent. For skewed distributions, correlations among the mean and standard deviation were expected, which may cause the range of the group outcome variable to be different, making the comparison of the regression weight difficult. In order to compare the conditions under both the normal and skewed contexts, 10,000 groups were simulated using normal, moderate skew $[\chi^2(10)]$, and heavy skew $[\chi^2(3)]$ distributions. The effect size of the dispersion measure was set to be .5. The observed correlation between group mean and standard deviation was .01, .43 and .70 for normal, moderate, and heavily skewed distributions respectively. For the normal case, the outcome variable had a mean of -.004 and standard deviation of 0.96 (minimum=-2.72, maximum=2.90). For the moderately skewed case, the outcome variable had a mean of -.008 and standard deviation of 0.99 (minimum=-2.81, maximum=2.89). For the heavily skewed case, the outcome variable had a mean of -.009 and standard deviation of 1.01 (minimum=-2.87, maximum=2.96). The results suggested that the range of the outcome variable was comparable across different distributions.

### 3.1.4 Rescaling continuous individual rating to 5-point ordinal scale

In their dispersion prediction model simulation, Roberson et al (2007) transformed the normally distributed group observations into responses that conformed to a Likert-type, 7-point scale. The current study used the factor analysis response function approach to scale the data to a five point scale (Wirth & Edwards, 2007). This approach specifies the complete *p* dimensional response pattern (where *p* is the number of observed variables) and assumes that responses to different variables are independent for given latent variables (conditional independence). Within this approach, the unit of analysis is the entire response pattern of a person. As such, no loss of information occurs. Based on whether the cumulative response function is normal or logistic, this approach is further categorized into the Normal Ogive Approach (NOR) and the Proportional Odds Model Approach (POM). The current study used the POM approach as a normal distribution of latent scores is not assumed. With $X_{ij}$ (the continuous individual-level rating) as the true latent scores of subject *i* in group *j*, and items *k* with *C* categories (*C* = 5 in this study),

$$\ln\left[\frac{\nu_{kc}(X)}{1-\nu_{kc}(X)}\right] = \alpha_{kc} - \beta_k X_{ij}\,,\ c = 1, 2, \cdots, C-1 \qquad [3]$$

$\alpha_{kc}$ are intercept parameters for each category of an item *k*, and must satisfy $\alpha_{k1} < \alpha_{k2} < \cdots < \alpha_{k(C-1)} < \alpha_{kC} = \infty$. The $\beta_k$ parameters are factor loadings. $\nu_{kc}(X)$ is referred to as the cumulative response function and the category response function is:

$$\begin{aligned} \pi_{k1}(X) &= \nu_{k1}(X) \\ \pi_{kc}(X) &= \nu_{kc}(X) - \nu_{k(c-1)}(X), c = 2, 3, \cdots, C \end{aligned} \qquad [4]$$

In the common factor analysis model (Takane & de Leeuw, 1987), the ordered categorical data is a reflection of the underlying variables that are normally distributed, and the underlying continuous response variable is obtained by multiplying the factor loading ($\lambda_k$) with the latent factor score plus an error term. The observed polytomous variable is obtained by comparing the underlying variable with threshold values ($\tau_{kc}$). A common factor analysis model was not used because a normal distribution of the underlying variable was not assumed. The $\alpha_{kc}$ and $\beta_k$ parameters in the aforementioned response function approach can be transformed from the threshold values $\tau_{kc}$, and the factor loadings, $\lambda_k$, in the classical common factor analysis approach as follows (Takane & de Leeuw, 1987):

$$\begin{aligned} \alpha_{kc} &= \tau_{kc} / \psi \\ \beta_k &= \lambda_k / \psi \end{aligned} \quad , \qquad [5]$$

where in the condition that has only one factor (i.e., unidimensional factorial structure),

$$\psi = \sqrt{1-\lambda_k^2} \qquad [6]$$

The factor loadings, $\lambda_k$, and threshold values, $\tau_{kc}$, of all five items are provided in

Table 7. The different threshold values for normal, moderately skewed, and heavily skewed distributions were adopted to achieve the desired skewness. The procedure of rescaling was as follows:

1. Transform the standardized parameters $\tau$ and $\lambda$ to unstandardized parameters $\alpha$ and $\beta$ using Equation [5].
2. With $X_{ij}$ as latent scores, compute the cumulative probabilities, $\nu_{kc}$, $c = 1,2,\cdots,C$ using equation [3].
3. Draw a uniform random number *u* and generate a response $x_{ijk} = c$ if $\nu_{kc} < x_{ijk} < \nu_{k(c+1)}$, $c = 1,2,\cdots,C-1$, where $x_{ij}$ is the observed item response of individual *i* in group *j* on item *k*.

After the item responses were generated, individual responses to the first item were used to compute dispersion index for the 1-item simulation conditions, and average of individual responses to all five items were used to compute dispersion index for the 5-item simulation conditions. As the individual latent scores used to generate these item responses are the same in 1-item and 5-item cases, this simulation factor was considered as a within-subject factor.

Table 7: Factor loadings and threshold values for five items

| Distribution | Item | Factor Loading | $\tau 1$ | $\tau 2$ | $\tau 3$ | $\tau 4$ | Skew |
|---|---|---|---|---|---|---|---|
| Normal | 1 | .8 | -1.5 | -0.5 | 0.5 | 1.5 | 0.006 |
| | 2 | .7 | -1.4 | -0.4 | 0.6 | 1.6 | 0.073 |
| | 3 | .6 | -1.3 | -0.3 | 0.7 | 1.7 | 0.136 |
| | 4 | .7 | -1.6 | -0.6 | 0.4 | 1.4 | -.056 |
| | 5 | .6 | -1.7 | -0.7 | 0.3 | 1.3 | -.127 |
| | Average | | | | | | -.008 |
| Moderate skew | 1 | .8 | -0.5 | 0.5 | 1.5 | 2.5 | 0.912 |
| | 2 | .7 | -0.4 | 0.6 | 1.6 | 2.6 | 0.810 |
| | 3 | .6 | -0.3 | 0.7 | 1.7 | 2.7 | 0.895 |
| | 4 | .7 | -0.7 | 0.3 | 1.3 | 2.3 | 1.023 |
| | 5 | .6 | -0.8 | 0.2 | 1.2 | 2.2 | 1.112 |
| | Average | | | | | | 0.876 |
| Heavy skew | 1 | .8 | 0.2 | 1.2 | 2.2 | 3.2 | 1.483 |
| | 2 | .7 | 0.3 | 1.3 | 2.3 | 3.3 | 1.562 |
| | 3 | .6 | 0.4 | 1.4 | 2.4 | 3.4 | 1.675 |
| | 4 | .7 | 0.1 | 1.1 | 2.1 | 3.1 | 1.403 |
| | 5 | .6 | 0.0 | 1.0 | 2.0 | 3.0 | 1.269 |
| | Average | | | | | | 1.431 |

### 3.1.5 Verification of data generation technique

A simulation was conducted to verify the data generation. The data generation verification was evaluated using the following criteria: 1) the visual shape of the distribution; 2) the quantified skew; and 3) the observed distributional variance.

This verification simulation incorporated 1,000 aggregated observations and 100 nested data points. The data were generated for normal, moderate skew, and heavy skew conditions while the effect of aggregated level dispersion ($\beta 2$) was set to .3. The last column of Table 7 presents the skewness of each item and the 5-item average. Appendix A includes the histograms of Item 1 and the 5-item average for normal, moderately skewed and heavily skewed conditions. The quantified skew and figures in Appendix A suggest that each of the corresponding shapes visually conform to what would be expected from each of the distributions specified. Where the data were specified to be normal, the observed distribution visually appears bell shaped and symmetrical around the mean. The observed distributions corresponding to the skewed distributions also appear as expected for the moderate skew and the heavy skew distributions.

Table 8 presents the observed average variance and ICC of the generated data. The observed average variance is similar to the average variance generated from uniform distribution. It can be observed that the ICC has similar values for different distributions.

Table 8: Verification of dispersion measures from normal and skewed distributions

| DISTRIBUTION | Specified average group dispersion | Observed average variance | ICC(1) |
|---|---|---|---|
| Normal | 0.5 | 0.50 | 0.48 |
| Moderate Skew | 0.5 | 0.51 | 0.47 |
| Heavy Skew | 0.5 | 0.51 | 0.47 |

# 4.0 RESULTS

This chapter presents the results from the Monte Carlo studies conducted. The simulation studies included seven potential independent variables of interest, each with multiple levels, resulting in a 3 (normal, moderate, and severe skew) x 4 (effect sizes) x 4 (number of aggregated observations) x 3(number of nested data points) x 2 (number of items) x 6 (dispersion indexes) x 2 (covariate of mean/median) design.

In the following sections, the assessment of linearity and homoscedasticity is presented first (section 4.1). The correlations between each of the dispersion indexes are then reviewed (section 4.2). In section 4.3, the Type I error rate results are presented. In section 4.4 the results of a mixed effects ANOVA on the evaluation outcome criteria including power, *VIF*, $R^2$, and $sr^2$ are presented.

## 4.1 ASSESSMENT OF LINEARITY AND HOMOSCEDASTICITY

For each the dispersion indexes, and across the distribution shapes, the relationship between the dispersion index and the simulated outcome was linear > 98% of the time (where $\lambda = 1$). This result suggests that non-linearity is not a systematic concern with dispersion prediction models. This result applies across dispersion indexes and simulated conditions. (Please refer to the left columns in the tables presented in Appendices G, H, and I which display the results of the multiple regression assumptions tests for linearity and homoscedasticity for the normal, moderate, and heavy skewed distribution shapes respectively.)

Consistent with the assumption of linearity, across all indexes, dispersion prediction multiple regression models generally do not systematically violate the assumption of homoscedasticity. The tables in the right of Appendices G, H, and I display the results of the tests for heteroscedasticity. For each dispersion index, the tables show the frequency with which White's test for heteroscedasticity was significant ($p < .05$), where a 1 indicates significance and 0 indicates non-significant. In the normal distribution condition, and the 1 item context the highest frequencies of significant tests corresponded to the *ADmd*, the *MAD*, and the *awg*: 7.4%, 8.7%, and 7.5% respectively. For all other indexes across simulated conditions the frequency of significant tests was generally less than 6%.

## 4.2 CORRELATION ANALYSIS

Table 9 and Table 10 reflect the Pearson correlations corresponding to each of the dispersion indexes averaged across conditions for each distribution shape simulated (Normal, Moderate Skew, and Heavy Skew) and for each scale (1 item and 5 items). Spearman correlation among the dispersion indexes were also computed, and found to be similar to Pearson correlations, and thus not reported.

As can be seen from the correlation tables, the correlations are positive and very high for the measures of *SD*, *ADm*, and *ADmd*. These correlations remain strong across the normal, moderate and heavy skew conditions. They also remain strong across the 1 and 5 item measures. The correlations are much lower between these three measures (the *SD*, *ADm*, and *ADmd*) and the *MAD*, *awg*, and *CV*.

*MAD*. There is evidence of a slight increase in correlation between *MAD* and *SD*/*ADm*/*ADmd* in the 1 polytomous item context between the normal condition and the skewed conditions. There is also an increased correlation between the *MAD* and the *SD*/*ADm*/*ADmd* in the 5 item context when compared to the 1 item context.

*awg*. There is an expected negative correlation between *awg* and the rest of the items, however the correlation is weaker than expected across the skew conditions and the 1 and 5 polytomous item contexts. Roberson et al., (2007) found a stronger negative correlation between the *awg* and the remaining dispersion measures in the seven response scale, multiple item, normal distributed context. The correlations between the *awg* and the remaining dispersion measures are generally between -.20 and -.30 in the normally distributed 1 and 5 polytmous item contexts. These correlations become weaker in the moderate and the heavy skewed conditions. The correlations between the *awg* and the remaining dispersion measures reduce to very small negative—zero correlation (and in some cases is a positive correlation) in the heavy skew condition.

*CV*. Of all the measures, the correlation of *CV* changes most between the 1 item and 5 item contexts as well as among the levels of distributional skew. The correlation between the *CV* and the *SD*, *ADm*, and *ADmd* is weak in the normal 1 item context and becomes strong and negative as the skew of the distribution moves to moderate and heavy. The correlation between the *CV* and the *SD*, *ADm*, and *ADmd* is moderately positive in the normal 5 item context and reduces to nearly zero in the moderate skew conditions and, then becomes weak and negative as the distribution becomes heavily skewed.

The sporadic correlations among the dispersion measures suggest that there are potential differences in performance in dispersion prediction models across conditions.

Table 9: Correlations among dispersion indexes by distribution shape in the1 item context

Normal 1 item

| | SD | Adm | Admd | MAD | awg |
|---|---|---|---|---|---|
| SD | | | | | |
| Adm | 0.94 | | | | |
| Admd | 0.93 | 0.98 | | | |
| MAD | 0.37 | 0.36 | 0.39 | | |
| awg | -0.22 | -0.22 | -0.20 | -0.14 | |
| CV | 0.19 | 0.19 | 0.18 | -0.01 | -0.20 |

Moderate Skew 1 item

| | SD | Adm | Admd | MAD | awg |
|---|---|---|---|---|---|
| SD | | | | | |
| Adm | 0.96 | | | | |
| Admd | 0.94 | 0.97 | | | |
| MAD | 0.56 | 0.52 | 0.62 | | |
| awg | -0.21 | -0.20 | -0.19 | -0.20 | |
| CV | -0.50 | -0.51 | -0.58 | -0.63 | 0.17 |

Heavy Skew 1 item

| | SD | Adm | Admd | MAD | awg |
|---|---|---|---|---|---|
| SD | | | | | |
| Adm | 0.97 | | | | |
| Admd | 0.92 | 0.96 | | | |
| MAD | 0.50 | 0.48 | 0.62 | | |
| awg | 0.02 | 0.01 | 0.02 | -0.10 | |
| CV | -0.66 | -0.75 | -0.80 | -0.58 | 0.03 |

Table 10: Correlations among dispersion indexes by distribution shape in the 5 item context

Normal 5 item

| | SD | Adm | Admd | MAD | awg |
|---|---|---|---|---|---|
| SD | | | | | |
| Adm | 0.97 | | | | |
| Admd | 0.97 | 1.00 | | | |
| MAD | 0.68 | 0.75 | 0.76 | | |
| awg | -0.29 | -0.29 | -0.28 | -0.20 | |
| CV | 0.52 | 0.51 | 0.51 | 0.36 | -0.30 |

Moderate Skew 5 item

| | SD | Adm | Admd | MAD | awg |
|---|---|---|---|---|---|
| SD | | | | | |
| Adm | 0.97 | | | | |
| Admd | 0.97 | 1.00 | | | |
| MAD | 0.65 | 0.72 | 0.74 | | |
| awg | -0.09 | -0.09 | -0.09 | -0.06 | |
| CV | 0.08 | 0.06 | 0.03 | -0.05 | 0.05 |

Heavy Skew 5 item

| | SD | Adm | Admd | MAD | awg |
|---|---|---|---|---|---|
| SD | | | | | |
| Adm | 0.97 | | | | |
| Admd | 0.95 | 0.99 | | | |
| MAD | 0.62 | 0.70 | 0.74 | | |
| awg | 0.05 | 0.04 | 0.04 | 0.02 | |
| CV | -0.15 | -0.24 | -0.29 | -0.37 | 0.05 |

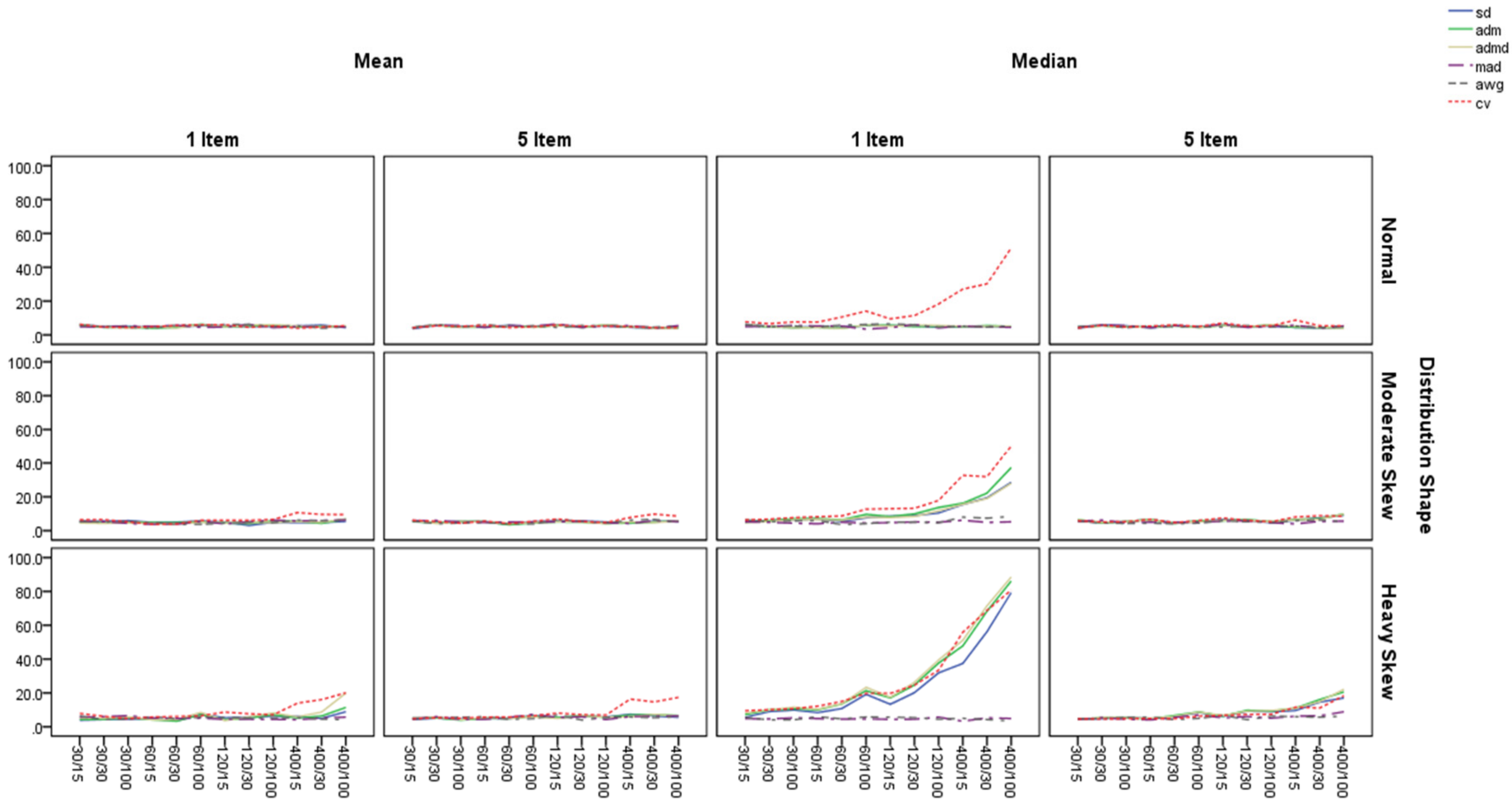
## 4.3 TYPE I ERROR

Figure 4 presents the level of Type I error for each dispersion index among all conditions in the simulation. The first two columns correspond to the Type I error results from the regression in which the mean was used as the central tendency covariate. The second two columns correspond to the Type I error results from the regression in which the median was used as the central tendency covariate. The table provided in Appendix B supplements Figure 4. Appendix B shows the Type 1 error rates for each cell in the simulation design. Using Figure 4 and the data provided in Appendix B, the following can be observed.

*Mean central tendency covariate.* When the mean is used as the central tendency control variable the average Type I error for the *SD*, *ADm*, *ADmd*, *MAD*, and *awg* is relatively stable across distribution shape and between the 1 and 5 item contexts. There is a slight increase in Type I error rate for each of the dispersion indexes in the heavy skew condition as the overall sample size (number of aggregated observations X number of nested data points) increases. This slight increase is more apparent for the 1 item context when compared to the 5 item context. Within the 5 item context the Type 1 error remains relatively stable and near the .05 nominal rate for each of the dispersion indexes except for the *CV*. The overall Type I error rate for the *CV* increases most dramatically through the levels of skew for both the 1 and 5 item context.

*Median central tendency covariate.* The pattern of Type I error is much different when the multiple regression model controls for the median rather than the mean, especially in the 1 item context. In the one item context each of the measures shows an inflation of Type I error rate as the distribution shape moves from normal to moderate and heavy skewed. The Type I error is further inflated as the total sample size increases. These trends are true for all measures except the *awg* and the *MAD* in the 1 item context. The inflation of Type I error across the levels of skew and sample size is much less pronounced in the 5 item context when compared to the 1 item context. For the *SD*, *ADm*, and *ADmd*, there is still a slight inflation of Type I error in the 5 item context in the heavy skew condition when the total sample size falls between approximately 6,000 (e.g., 400 aggregated observations X 15 nested data points) and 40,000 (i.e., 400 aggregated observations X 100 nested data points). Of all the dispersion indexes, the *CV* shows the largest and most sporadic inflation of Type I error across the simulated conditions when controlling for the median as the central tendency covariate.

Figure 4: Type I error across all conditions



## 4.4 MIXED EFFECTS ANOVA

A mixed ANOVA with four between-subject factors and three within-subject factors was executed for each of the four outcomes (power, *VIF*, $sr^2$ and model $R^2$). Table 11 shows the between subject and within subject factors separately along with the levels of each factor. Appendices C, D, E, and F include supplementary tables with the power, $sr^2$, $R^2$, and *VIF* values (respectively) for each cell in the complete ANOVA design.

Table 11 : Mixed effects ANOVA factors and levels

| Simulation Parameters and Levels for 1 and 5 items separately | |
|---|---|
| Between Subject Factors | Levels |
| Number of Nested Data Points (NDP) | 15, 30, 100 |
| Number of Observations (NOB) | 30, 60, 120, 400 |
| Effect Size (Effect) | .10, .30, and .50 |
| Shape of distribution (Shape) | Normal, Moderate Skew, Heavy Skew |
| Within Subject Factors | |
| Dispersion Indexes (Index) | *SD, ADm,* $AD_{Md}$, *CV, MAD,* $a_{WG}$, |
| Central Tendency Control (CT) | *Mean, Median* |
| Number of items (Item) | 1, 5 |

As the research questions involve the impact of the dispersion index, distribution shape, the number of items, and central tendency control, the effects related with these factors, including their main effects, 2-way, and 3-way interactions were examined. Because the primary research inquiry focuses on the differential performance of the dispersion indexes among the other factors identified in this study, all interaction effects involving the dispersion indexes were examined.

In the ANOVA models with power as the outcome, as there is only one observation in each simulation condition, higher-order interaction effects cannot be estimated. Therefore, only three-way interaction between the dispersion index and any two of the other factors were considered along with all the involved lower-order effects. For the other outcome variables (i.e., *VIF*, $sr^2$ and model $R^2$) there were 1000 observations in each simulation condition and a full factorial ANOVA was used. In order to remain consistent with the ANOVA executed on power, all applicable three-way interactions were examined along with the main and two-way interaction effects. For practical interpretation purposes, only effects with large effect size ($\eta_p^2 >$ .25) will be discussed.

Table 12 shows the partial eta squared ($\eta_p^2$) for the set of ANOVAs performed. As can be seen from the table, there are a number of large effects for each of the outcomes. The ANOVAs for each of the outcomes will be discussed separately in the next four subsections. Each of the effects relevant for discussion purposes is bolded and italicized.

Table 12: $\boldsymbol{\eta_p^2}$ for mixed effects ANOVAs

| Factor | Power | $sr^2$ | $R^2$ | VIF |
|---|---|---|---|---|
| | | *Main Effects* | | |
| Index | .96 | .50 | .49 | .94 |
| CT | .77 | .30 | .22 | .34 |
| Item | .91 | .16 | ***.28*** | .65 |
| Shape | .04 | .00 | .01 | .60 |
| NOB | .95 | .15 | .11 | .11 |
| NDP | .80 | .15 | .06 | .54 |
| Effect | .95 | .38 | .08 | .00 |
| | | *Two-Way Interactions* | | |
| Index X CT | .60 | .16 | ***.30*** | .83 |
| Index X Item | .58 | .13 | .04 | .34 |
| Index X Shape | .34 | .03 | .03 | .62 |
| Index X NOB | .86 | .00 | .00 | .04 |
| Index X NDP | ***.60*** | .09 | .11 | ***.32*** |
| Index X Effect | .87 | ***.27*** | ***.26*** | .00 |
| CT X Item | .87 | .12 | .03 | .23 |
| CT X Shape | .70 | ***.26*** | .01 | .10 |
| Item X Shape | .84 | .05 | .02 | .35 |
| | | *Three-Way Interactions* | | |
| Index X CT X Item | ***.82*** | .19 | .09 | ***.54*** |
| Index X CT X Shape | ***.52*** | .11 | .11 | ***.56*** |
| Index X CT X NOB | .24 | .00 | .00 | .01 |
| Index X CT X NDP | .03 | .01 | .01 | .18 |
| Index X CT X Effect | .13 | .03 | .03 | .00 |
| Index X Item X Shape | ***.68*** | .06 | .03 | ***.55*** |
| Index X Item X NOB | ***.52*** | .00 | .00 | .02 |
| Index X Item X NDP | .25 | .00 | .00 | .09 |
| Index X Item X Effect | ***.46*** | .05 | .04 | .00 |
| Index X Shape X NOB | .15 | .00 | .00 | .02 |
| Index X Shape X NDP | .05 | .00 | .00 | .21 |
| Index X Shape X Effect | .07 | .01 | .01 | .00 |
| Index X NOB X NDP | .15 | .00 | .00 | .02 |
| Index X NOB X Effect | ***.58*** | .00 | .00 | .00 |
| Index X NDP X Effect | .15 | .07 | .07 | .00 |
| CT X Item X Shape | ***.77*** | .07 | .01 | .16 |

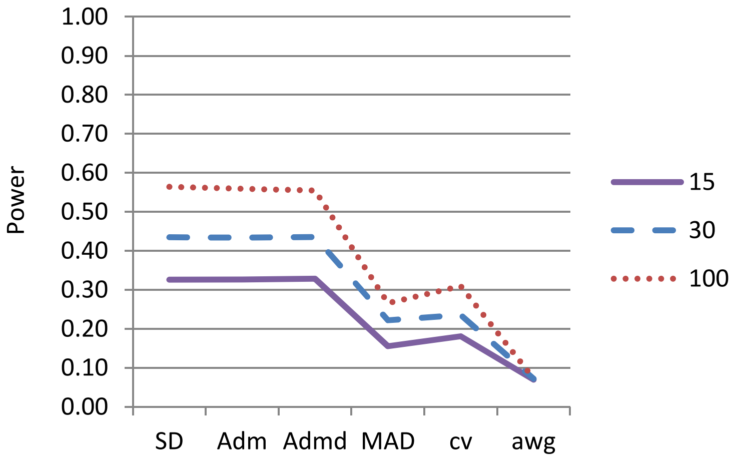
NOTE: Bolded and italicized effects are discussed below.

### 4.4.1 Power

Table 12 shows that the mixed effects ANOVA analysis on power resulted in numerous statistically and practically significant effects. However, each of the significant main effects are included within the significant two-way interactions. Each of the significant two-way interactions (except dispersion index x nested data points) is included within the significant three-way interactions. To illustrate, the two-way interaction for dispersion index x number of aggregated observations is significant ($\eta_p^2$ = .86, $p$ < .001). This effect is captured within the significant three-way interaction between dispersion index, number of observations, and effect size ($\eta_p^2$ = .58, p < .001), and in the three-way interaction between dispersion index, number of observations, and number of items ($\eta_p^2$ = .52, $p$ < .001). Thus, for the sake of parsimony, only unique effects are interpreted. This is true of the power outcome as well as the $sr^2$, $R^2$, and *VIF* outcomes. In Table 12 each of the effects interpreted are bolded and italicized.

Figure 5 shows the two-way interaction between dispersion index and number of nested data points. The Figure shows that there is an increase in statistical power as the number of nested data points increases. This is true for the *SD*, *ADm*, *ADmd*, *MAD*, and *CV*. When compared to the *MAD*, *CV*, and *awg*, the *SD*, *ADm*, and *ADmd* have a higher starting power value in the 15 nested data points condition. The *SD*, *ADm*, and *ADmd* also have higher gain in power between the 15 and 30, and between 30 and 100 nested data point conditions when compared to the gains of the *MAD, CV*. The power corresponding to the *awg* dispersion index does not increase as the number of nested data points increases.

Figure 5: Two-way interaction between dispersion index and number of nested data points on Power




| | Power | | |
|---|---|---|---|
| | 15 | 30 | 100 |
| SD | 0.33 | 0.43 | 0.56 |
| Adm | 0.33 | 0.43 | 0.56 |
| Admd | 0.33 | 0.44 | 0.55 |
| MAD | 0.16 | 0.22 | 0.27 |
| CV | 0.18 | 0.24 | 0.31 |
| awg | 0.07 | 0.07 | 0.07 |

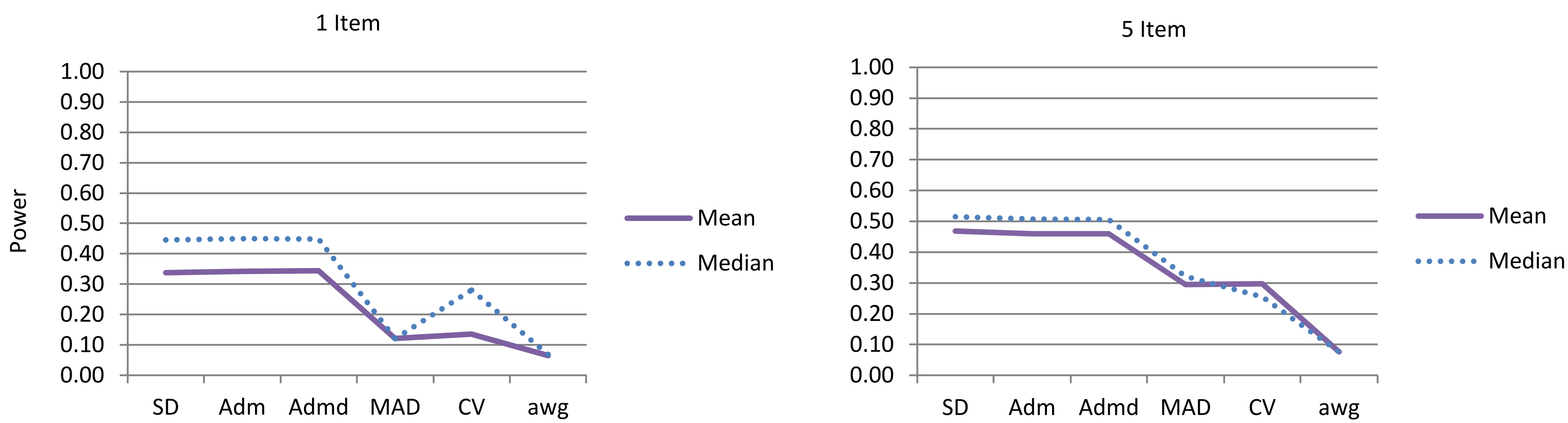
Figure 6 shows the three-way interaction between dispersion index, number of items, and central tendency covariate on statistical power. Consistent with Figure 5, there are substantial power advantages for the *SD*, *ADm*, and *ADmd* over the *MAD*, *CV*, and *awg* across the conditions in the study.

Figure 6 shows that across distribution shapes in the 1 item condition, there are substantial power advantages when controlling for the median for the *SD*, *ADm*, *ADmd*, and *CV* (11% for the *SD*, *ADm*, and *ADmd*; and 14% for the *CV*). There is no such gain in power when the *MAD* or *awg* is used as the dispersion index. In the one item context the average power for the *MAD* and *awg* remains stable and low.

There is a different pattern among the conditions revealed in the 5 item context. First, across the dispersion indexes (except for the *awg*) there is a noticeable increase in power over the one item context. The *awg* is the only dispersion index to not perform substantially different from 1 to 5 item context and its average power remains the lowest of the dispersion indexes.

Similar to the 1 item context, across the levels of distribution shape, when using the median as the level covariate, there are power advantages over the mean for the *SD*, *ADm*, and *ADmd*. These advantages are less than the 1 item context however. Distinct from the 1 item context, the *MAD* shows slight gains in power when using the median as the level covariate in the 5 item context. Opposite from the 1 item context where the *CV* increased in power by 14% when using the median as the level covariate, it decreased in average power by 5% when the median was used as the level covariate.

Figure 6: Three-way interaction between dispersion index, central tendency covariate, and number of items on Power




| | Power, 1 item | | Power, 5 Item | |
|---|---|---|---|---|
| | Mean | Median | Mean | Median |
| SD | 0.34 | 0.45 | 0.47 | 0.51 |
| Adm | 0.34 | 0.45 | 0.46 | 0.51 |
| Admd | 0.34 | 0.45 | 0.46 | 0.51 |
| MAD | 0.12 | 0.12 | 0.29 | 0.32 |
| CV | 0.14 | 0.28 | 0.30 | 0.25 |
| awg | 0.06 | 0.07 | 0.08 | 0.08 |

Figure 7 shows the three-way interaction between dispersion index, distribution shape, and central tendency covariate on power. The left panel of the Figure shows the pattern power for each dispersion index across the levels of skew when using the mean as the level covariate. The right panel of the Figure shows the pattern of dispersion index power across the levels of skew when using the mean as the covariate. The panels show very different patterns.

Similar to the previous effects on power, the *SD*, *ADm*, and *ADmd* display much higher average power when compared to the *MAD*, *CV,* and *awg*. There is also a similar consistent pattern of power between the *SD*, *ADm*, and *ADmd* among the levels of the level covariate and distribution shape which is distinct compared to the patterns of the *MAD*, *CV*, and *awg*.

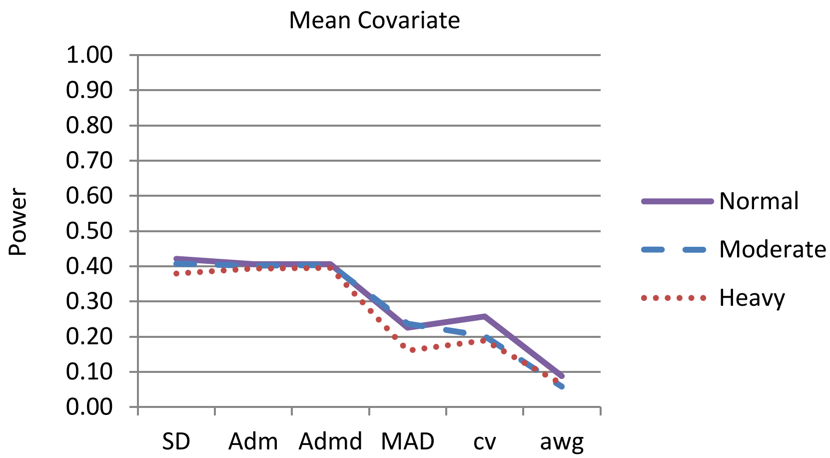
*SD, ADm, and ADmd.* When the mean is used as the level covariate there is a very slight (~1% on average) advantage of the *SD* over the *ADm*, and *ADmd* in the normal distribution. With the mean level covariate, in the moderately skewed distribution the average power decreases by 1% for each of the dispersion indexes. Comparing the average power between the heavy skewed and normal distribution: the *SD* dropped 4% average power; the *ADm* dropped 2%; and the *ADmd* dropped 1%.

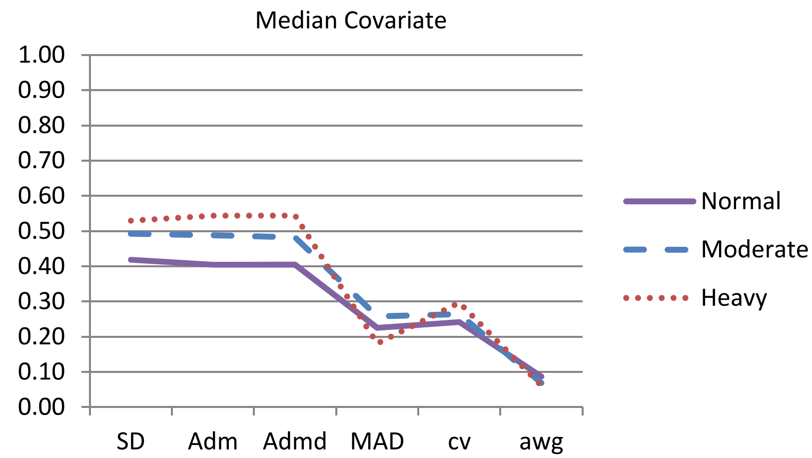
When the distribution is normal, there is no practical difference in the average power pattern among the *SD*, *ADm* and *ADmd*. As the distribution changes in shape, however, there are power advantages in using the median as the level covariate. In the moderately skewed distribution controlling for the median provides an additional ~8% in average power for the *SD*, *ADm*. and *ADmd* compared to the condition in which the mean was used as the level covariate. In the heavy skewed distribution there is an additional ~15% in average power for the *SD*, *ADm*, and *ADmd* compared to the condition in which the mean was used as the level covariate.

This pattern suggests that controlling for median as the level covariate in both the moderate and heavy skewed distributions provides greater average power than controlling for the mean in any distribution shape. For the *SD*, *ADm*, and *ADmd*, when the distribution is normal using either the mean or median provides the same average power. As the distribution shape moves from moderate to heavy skew this power decreases when controlling for the mean, but increases when controlling for the median.

*MAD, CV, and awg*. Among the conditions shown in Figure 7 the levels of average power for each of these dispersion indexes is much lower than the *SD*, *ADm*, and *ADmd*. The pattern of average power for the *CV* is similar to the *SD*, *ADm*, and *ADmd*: power starts at a similar value between the mean and median level covariate in the normal condition; power decreases as the distribution becomes skewed when using the mean as the level covariate; power increases as the distribution becomes skewed when using the median as the level covariate. In the normal distribution, the power the *MAD* is consistent between the mean and median level covariate conditions. When compared to the normal condition, the power for the *MAD* increases slightly when controlling for the mean (1%) and slightly more when controlling for the median (4%) in the moderate skewed distribution. There is an unexpected decline in power for the *MAD* between the moderate and heavy skewed conditions, however. The *awg* shows the same performance pattern across both the mean and median level covariate conditions. The average decreases slightly as the distribution shape moves from normal to heavy skew. The average power for the *awg* is lowest among the dispersion indexes.

Figure 7: Three-way interaction between dispersion index, distribution shape, and central tendency covariate on Power



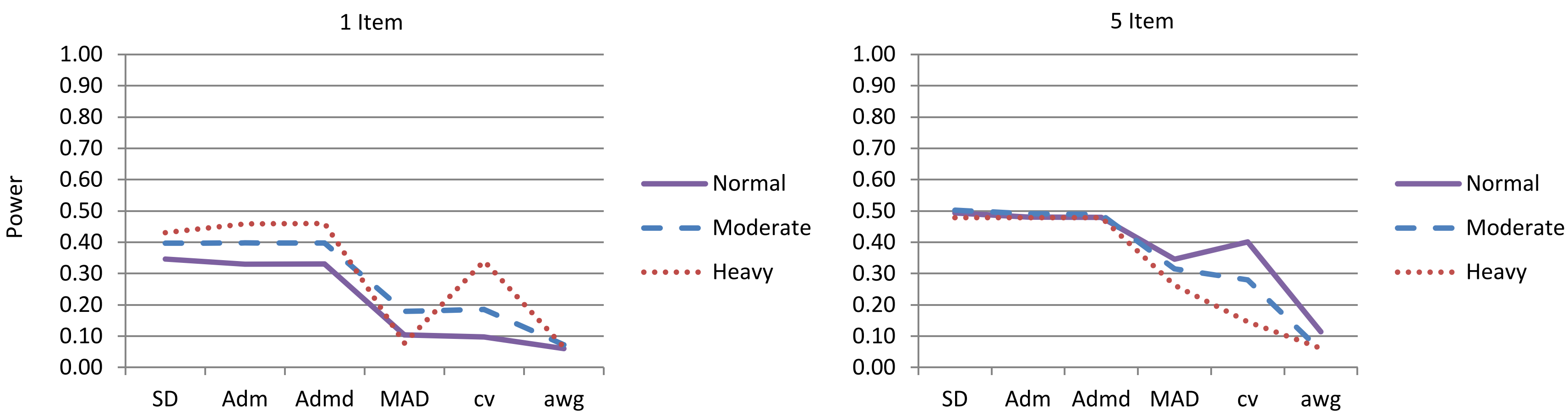

| | Power, Mean Covariate | | | Power, Median Covariate | | |
|---|---|---|---|---|---|---|
| | Normal | Moderate | Heavy | Normal | Moderate | Heavy |
| SD | 0.42 | 0.41 | 0.38 | 0.42 | 0.49 | 0.53 |
| Adm | 0.41 | 0.40 | 0.39 | 0.40 | 0.49 | 0.54 |
| Admd | 0.41 | 0.40 | 0.40 | 0.40 | 0.48 | 0.54 |
| MAD | 0.23 | 0.24 | 0.16 | 0.22 | 0.26 | 0.18 |
| CV | 0.26 | 0.20 | 0.19 | 0.24 | 0.26 | 0.30 |
| awg | 0.09 | 0.06 | 0.07 | 0.09 | 0.07 | 0.06 |

Figure 8 shows the three-way interaction between dispersion index, distribution shape, and number of items. Each the *SD*, *ADm* and *ADmd* show substantially higher average power than the *MAD*, *CV*, and *awg*. Within the Figure, the patterns among the *SD*, *ADm*, and *ADmd* are also similar.

*SD, ADm, and ADmd*. Across conditions within the Figure, there is a substantial increase in power between the 1 and 5 item context for each of the indexes. In the 1 item condition, the power increases for each of the indexes as the distribution shape moves from normal to heavy skewed. The average power for each of the *SD*, *ADm*, and the *ADmd* is relatively consistent in the 5 item context across the levels of skew.

*MAD, CV, and awg*. In the 1 item condition, the average power of the *MAD* increases 8% as the distribution shape moves from normal to moderate and then decreases 10% between the moderate and heavy skewed conditions. In the 5 item context the power of the *MAD* starts out substantial higher than any of the average power values displayed in the one item context for the index and then decreases systematically through the moderate and heavy conditions. The average power of the *MAD* in the 5 item heavy skewed condition is still much greater than the average power for the *MAD* in any of the 1 item conditions. The *CV's* pattern in power is completely opposite between the 1 and 5 item conditions. In the 1 item condition power increases substantially for the *CV* as the distribution shape moves from normal to heavy skew (increase by 24%). In the 5 item context, the average power for the *CV* decreases substantially as the distribution shape moves from normal to heavy skew (decrease of 25%). The power for the *awg* remains lowest and across conditions in the Figure.

Figure 8: Three-way interaction between dispersion index, distribution shape, and number of items on Power




| | Power, 1 Item | | | Power, 5 Item | | |
|---|---|---|---|---|---|---|
| | Normal | Moderate | Heavy | Normal | Moderate | Heavy |
| SD | 0.35 | 0.40 | 0.43 | 0.49 | 0.50 | 0.48 |
| Adm | 0.33 | 0.40 | 0.46 | 0.48 | 0.49 | 0.48 |
| Admd | 0.33 | 0.40 | 0.46 | 0.48 | 0.49 | 0.48 |
| MAD | 0.10 | 0.18 | 0.08 | 0.35 | 0.32 | 0.26 |
| CV | 0.10 | 0.19 | 0.34 | 0.40 | 0.28 | 0.15 |
| awg | 0.06 | 0.07 | 0.07 | 0.11 | 0.05 | 0.06 |

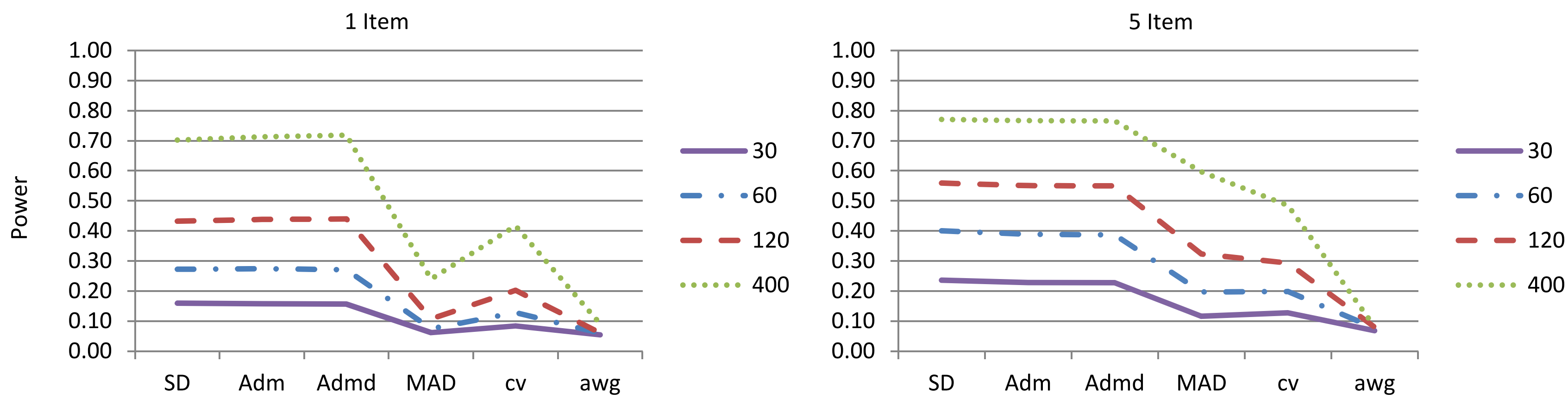
Figure 9 shows the three-way interaction between dispersion index, number of aggregated observations and the number of items from which the dispersion index was computed. As in the previous effects on statistical power, the power of the *SD*, *ADm*, and *ADmd* display a consistent pattern and substantially higher values when compared to the *MAD*, *CV*, and *awg*. For both the 1 and 5 item conditions, as would be expected, as the number of aggregated observations increases so does the power for each dispersion index.

As the number of aggregated observations increases, the increases in power are somewhat uniform (except for a larger increase between 120 and 400) in the 1 item context for the *SD*, *ADm*, and *ADmd*. In the 1 item context increasing the number of aggregated observations has less of an effect on the power for *MAD*, *CV*; this is especially true as the number of aggregated observations increases from 30 to 120. For the *CV* and *MAD* there is a noticeable gain in power between the 120 and 400 observation conditions. The *awg* shows minimal fluctuation in power across the levels of aggregated observations. In the 5 item context the increase in aggregated observations is associated with a uniform increases in power for the *SD*, *ADm*, *ADmd*, *MAD*, and *CV*. Similar to the 1 item context, in the 5 item context the *awg* shows minimal fluctuation among the levels of aggregated observations.

A very similar pattern is revealed in Figure 10. Figure 10 shows the three-way interaction between dispersion index, effect size, and number of items. In the 1 item condition the power of the *SD*, *ADm*, and *ADmd* increases uniformly as the effect size increases; the power increases only minimally for the *MAD*, *CV* and *awg* as the effect size increases. In the 5 item context, the power for each of the *SD*, *ADm*, *ADmd*, *MAD*, and *CV* increases uniformly as the effect size increases from .30 to .50 while the *awg* power increases minimally. Across all conditions the power of the *SD, ADm*, and *ADmd* is noticeably greater than the power of the *MAD*, *CV*, and *awg*.

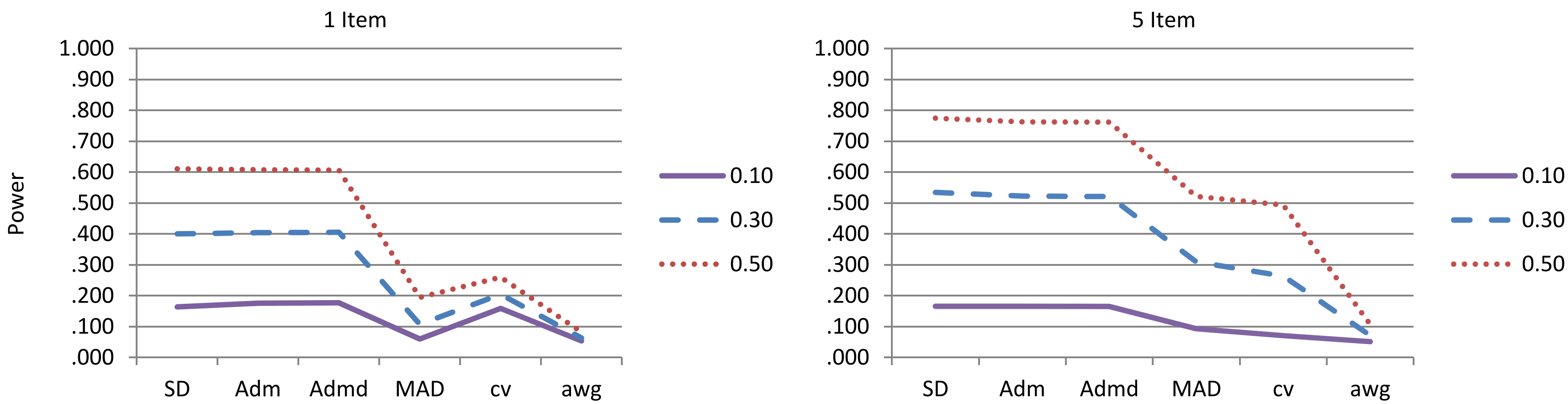
Figure 11 shows the three-way interaction between dispersion index, number of aggregated observations, and effect size. Figure 11 shows that when the effect size is .10 and the number of aggregated observations is equal to 30 and 60 there is little power difference between any of the indexes. In the 120 and 400 aggregated observation condition the *SD*, *ADm*, and *ADmd* display noticeable advantages in power *MAD, CV*, and *awg*. The differences in power between the *SD*/*ADm*/*ADmd* and *MAD*/*CV*/*awg* are much more pronounced in the .30 and .50 effect size conditions even in the 30 aggregated observation conditions. In the .30 condition, when using the *MAD* or *CV* 400 observations are required to approach the level of power the *SD*, *ADm*, and *ADmd* displayed with 120 observations. In the .50 condition, the power of the *MAD* and *CV* is ~15% below that of the *SD*, *ADm*, and *ADmd*. In the .30 condition there is also a minimal increase in power between the 30 and 60 aggregated observation conditions for the *CV* and *MAD*. Consistent with previous effects there is minimal fluctuation in power for the *awg* across conditions.

Figure 9: Three-way interaction between dispersion index, number of aggregated observations, and number of items on Power



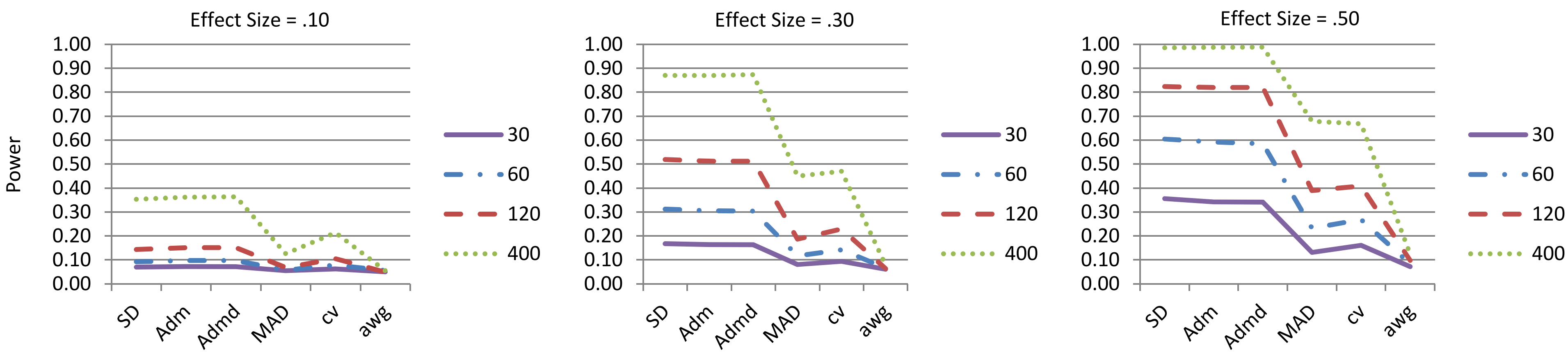

| | Power, 1 Item | | | | Power, 5 Item | | | |
|---|---|---|---|---|---|---|---|---|
| | 30 | 60 | 120 | 400 | 30 | 60 | 120 | 400 |
| SD | 0.16 | 0.27 | 0.43 | 0.70 | 0.24 | 0.40 | 0.56 | 0.77 |
| Adm | 0.16 | 0.27 | 0.44 | 0.71 | 0.23 | 0.39 | 0.55 | 0.77 |
| Admd | 0.16 | 0.27 | 0.44 | 0.72 | 0.23 | 0.39 | 0.55 | 0.77 |
| MAD | 0.06 | 0.07 | 0.11 | 0.24 | 0.12 | 0.20 | 0.32 | 0.60 |
| CV | 0.08 | 0.13 | 0.20 | 0.42 | 0.13 | 0.20 | 0.29 | 0.48 |
| awg | 0.05 | 0.06 | 0.06 | 0.09 | 0.07 | 0.08 | 0.08 | 0.08 |

Figure 10: Three-way interaction between dispersion index, effect size, and number of items on Power




| | Power, 1 Item | | | Power, 5 Item | | |
|---|---|---|---|---|---|---|
| | 0.10 | 0.30 | 0.50 | 0.10 | 0.30 | 0.50 |
| SD | 0.16 | 0.40 | 0.61 | 0.17 | 0.53 | 0.77 |
| Adm | 0.18 | 0.40 | 0.61 | 0.17 | 0.52 | 0.76 |
| Admd | 0.18 | 0.41 | 0.61 | 0.17 | 0.52 | 0.76 |
| MAD | 0.06 | 0.11 | 0.19 | 0.09 | 0.31 | 0.52 |
| CV | 0.16 | 0.20 | 0.26 | 0.07 | 0.26 | 0.49 |
| awg | 0.05 | 0.06 | 0.08 | 0.05 | 0.07 | 0.11 |

Figure 11: Three-way interaction between dispersion index, number of aggregated observations, and effect size on Power

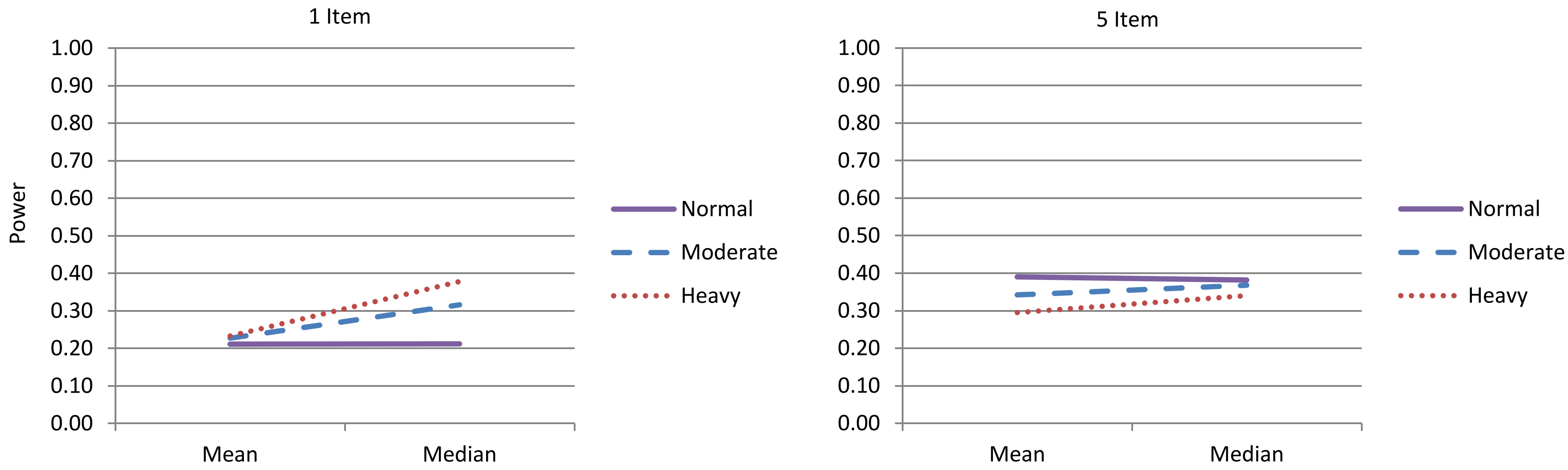



| | Power, Effect Size = .10 | | | | Power, Effect Size = .30 | | | | Power, Effect Size = .50 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 30 | 60 | 120 | 400 | 30 | 60 | 120 | 400 | 30 | 60 | 120 | 400 |
| SD | 0.07 | 0.09 | 0.14 | 0.35 | 0.17 | 0.31 | 0.52 | 0.87 | 0.36 | 0.60 | 0.82 | 0.99 |
| Adm | 0.07 | 0.10 | 0.15 | 0.36 | 0.16 | 0.31 | 0.51 | 0.87 | 0.34 | 0.59 | 0.82 | 0.99 |
| Admd | 0.07 | 0.10 | 0.15 | 0.36 | 0.16 | 0.30 | 0.51 | 0.87 | 0.34 | 0.59 | 0.82 | 0.99 |
| MAD | 0.05 | 0.06 | 0.07 | 0.13 | 0.08 | 0.12 | 0.19 | 0.45 | 0.13 | 0.23 | 0.39 | 0.68 |
| CV | 0.06 | 0.08 | 0.10 | 0.21 | 0.09 | 0.14 | 0.23 | 0.47 | 0.16 | 0.27 | 0.41 | 0.67 |
| awg | 0.05 | 0.06 | 0.05 | 0.06 | 0.06 | 0.07 | 0.06 | 0.08 | 0.07 | 0.08 | 0.10 | 0.12 |

Figure 12 shows the three-way interaction between central tendency covariate (mean/median), number of items (1/5), and distribution shape. Figure 12 shows that across the in the 1 item context the power averaged across the dispersion indexes is equal in the normal condition when using the mean or median as the covariate. In the moderately and heavy skewed distribution dispersion prediction models that control for the mean remain stable in power. In the moderately skewed distribution shape using the median as the level covariate has power advantages over the mean. The power advantages when controlling for the median are most pronounced in the heavy skewed distribution.

A slightly different pattern is revealed in the five item context. First the average power levels are much higher in the five item context when compared to the one item context. Similar to the 1 item context, in the normally distributed distribution 5 item condition, dispersion prediction models that use the median or mean as the level covariate are consistent in power. When using the mean as the level covariate in the five item context, as the distribution shape moves from normal to moderate skew to heavy skew there is a 9% decrease in average power across the dispersion indexes. When using the median as the level covariate there is a 4% decline in average power between the normal and heavy skewed distributions. In the moderate and heavy skewed distributions there is a 3% and 4% respective average power advantage when using the median as the level covariate over the mean.

Figure 12: Three-way interaction between central tendency covariate, number of items, and distribution shape on Power

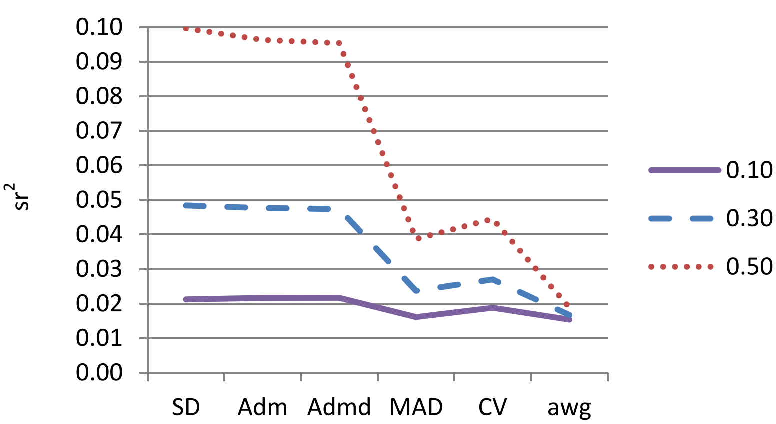



| | Power, 1 Item | | | Power, 5 Item | | |
|---|---|---|---|---|---|---|
| | Normal | Moderate | Heavy | Normal | Moderate | Heavy |
| Mean | 0.21 | 0.23 | 0.23 | 0.39 | 0.34 | 0.30 |
| Median | 0.21 | 0.32 | 0.38 | 0.38 | 0.37 | 0.34 |

### 4.4.2 $sr^2$

Because of the large number of cases used in the ANOVA, each of the effects on the $sr^2$ is statistically significant. There are fewer practically significant results however ($\eta_p^2$ > ~.25). Figure 13 shows the significant two-way interaction between dispersion index and effect size on $sr^2$. Figure 13 shows that where the effect size is equal to .10 there is very little difference in $sr^2$ between the dispersion indexes. As the effect size increases from .10 to .30 there is a zero to slight increase in $sr^2$ for the *MAD*, *CV*, and *awg*. As the effect size increases from .30 to .50 there is small increase in $sr^2$ for the *MAD* and *CV* and no increase for the *awg*. Conversely, as the effect size increases from .10 to .50 there is an associated noticeable increase in $sr^2$ for the *SD*, *ADm*, and *ADmd*.

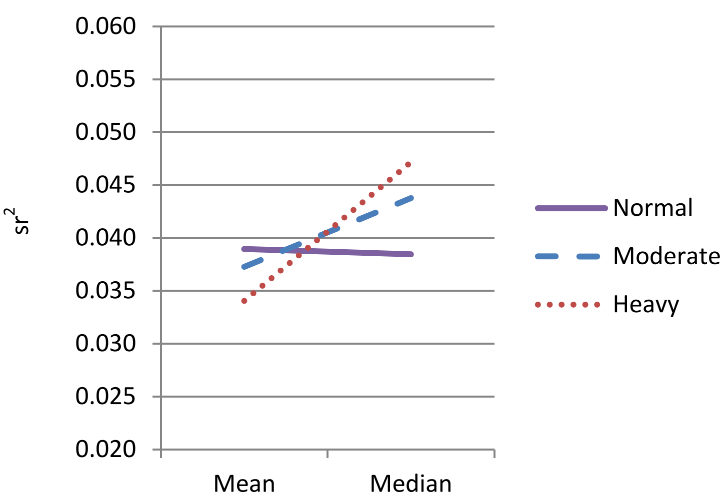
Figure 13: Two-way interaction between dispersion index and effect size on $sr^2$




| | $sr^2$ | | |
|---|---|---|---|
| | 0.10 | 0.30 | 0.50 |
| SD | 0.02 | 0.05 | 0.10 |
| Adm | 0.02 | 0.05 | 0.10 |
| Admd | 0.02 | 0.05 | 0.10 |
| MAD | 0.02 | 0.02 | 0.04 |
| CV | 0.02 | 0.03 | 0.04 |
| awg | 0.02 | 0.02 | 0.02 |

Figure 14 shows the two-way interaction between central tendency covariate and distribution shape on *$sr^2$*. When the dispersion indexes are computed from a normal distribution of nested data points the average *$sr^2$* is similar between dispersion prediction models that control for the mean or median. When the mean is used as the level covariate there is a slight overall decrease in *$sr^2$* between the normal and moderately skewed conditions and a noticeable decrease in between the normal and heavy skewed distributions. In an opposite pattern, when the median is used as the level covariate the level covariate there is an increase in *$sr^2$* between the normal and each of the skewed distributions.

Figure 14: Two-way interaction between central tendency covariate and distribution shape on $sr^2$



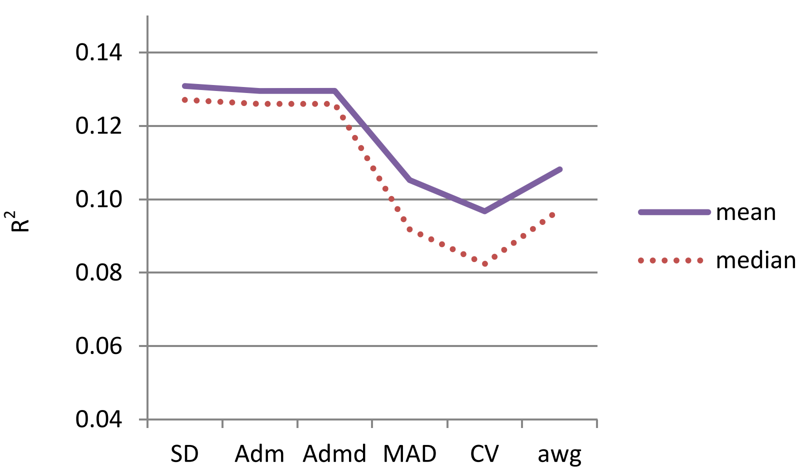

| $sr^2$ | Normal | Moderate | Heavy |
|---|---|---|---|
| Mean | 0.039 | 0.037 | 0.034 |
| Median | 0.038 | 0.044 | 0.047 |

### 4.4.3 $R^2$

Because of the large number of cases used in the ANOVA, each of the effects on the $R^2$ outcome are statistically significant. There are fewer practically significant results however ($\eta_p^2 > \sim.25$).

Figure 15 shows the two-way interaction between dispersion index and central tendency covariate on $R^2$. The average $R^2$ for the *SD*, *ADm*, and *ADmd* are somewhat stable across dispersion prediction models that use the mean or median as the level covariate. These $R^2$ values are noticeably higher than those that correspond to dispersion prediction models that use the *MAD*, *CV*, and *awg* as the dispersion index. For the *MAD*, *CV*, and *awg* there is a slight decrease (between 1% and 2%) in $R^2$ values for dispersion prediction models that use the median as the level covariate when compared to the mean.

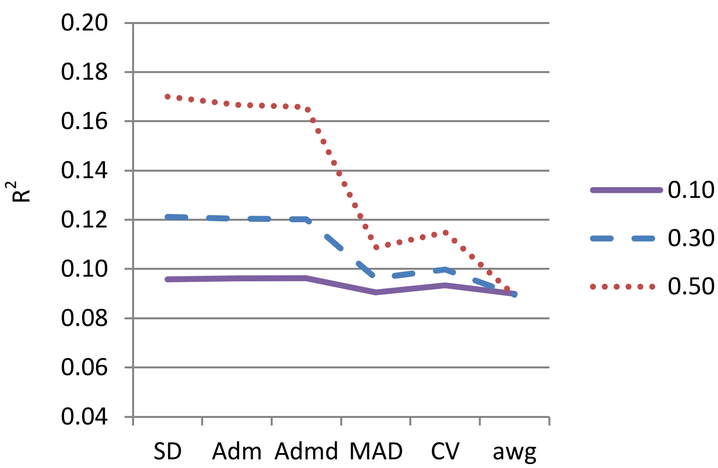
Figure 15: Two-way interaction between dispersion index and central tendency covariate on $R^2$




| | $R^2$ mean | $R^2$ median |
|---|---|---|
| SD | .13 | .13 |
| Adm | .13 | .13 |
| Admd | .13 | .13 |
| MAD | .11 | .09 |
| CV | .10 | .08 |
| awg | .11 | .10 |

Figure 16 shows the two-way interaction between dispersion index and effect size on $R^2$. As the predefined dispersion effect size increases, so does the dispersion prediction model $R^2$ for each of the indexes except the *awg*. The *awg* remains fixed throughout the levels of effect size. As the effect size increases, the increase in overall model $R^2$ is greater for the *SD*, *ADm*, and ADmd when compared to the *MAD* and *CV*. The difference between the $R^2$ for the .50 effect size and the .10 effect size for the *MAD* and *CV* was .02. The difference between the model $R^2$ for the .50 and .10 effect size for the *SD*, *ADm*, and the *ADmd* is .07.

Figure 16: Two-way interaction between dispersion index and effect size on $R^2$



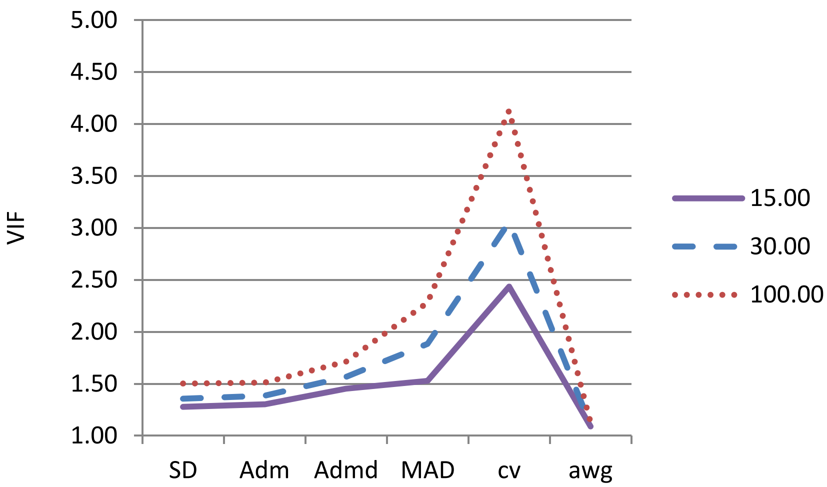

| | $R^2$ | | |
|---|---|---|---|
| | 0.10 | 0.30 | 0.50 |
| SD | 0.10 | 0.12 | 0.17 |
| Adm | 0.10 | 0.12 | 0.17 |
| Admd | 0.10 | 0.12 | 0.17 |
| MAD | 0.09 | 0.10 | 0.11 |
| CV | 0.09 | 0.10 | 0.11 |
| awg | 0.09 | 0.09 | 0.09 |

### 4.4.4 VIF

Because of the large number of cases used in the ANOVA, each of the effects on *VIF* is statistically significant. There are fewer practically significant results however ($\eta_p^2 > \sim.25$).

Figure 17 shows the two-way interaction between dispersion index and the number of nested data points on *VIF*. Figure 17 shows that, for each of the dispersion indexes, as the number of nested data points increases so does the correlation between the dispersion index and the level covariate. Across the levels of nested data points, the average *VIF* is similar between the *SD* and the *ADm* and is slightly higher for the *ADmd*. The *MAD* has a higher *VIF* than the *ADmd* across the levels of nested data points. The *CV* has the highest average *VIF* across the levels of nested data points. The *VIF* for the *CV* increases sharply to an average level greater than 4 as the number of nested data points reaches 100. The *VIF* for the *awg* is low, and remains comparatively low, through the levels of nested data points.

Figure 17: Two-way interaction between dispersion index and number of nested data points on VIF




| | VIF | | |
|---|---|---|---|
| | 15 | 30 | 100 |
| SD | 1.28 (.46) | 1.36 (.51) | 1.50 (.58) |
| Adm | 1.30 (.48) | 1.39 (.53) | 1.51 (.58) |
| Admd | 1.45 (.56) | 1.57 (.60) | 1.71 (.64) |
| MAD | 1.53 (.59) | 1.89 (.69) | 2.28 (.75) |
| CV | 2.44 (.77) | 3.06 (.82) | 4.13 (.87) |
| awg | 1.09 (.29) | 1.10 (.30) | 1.13 (.34) |

Note: Correlation between dispersion index and central tendency covariate in parentheses

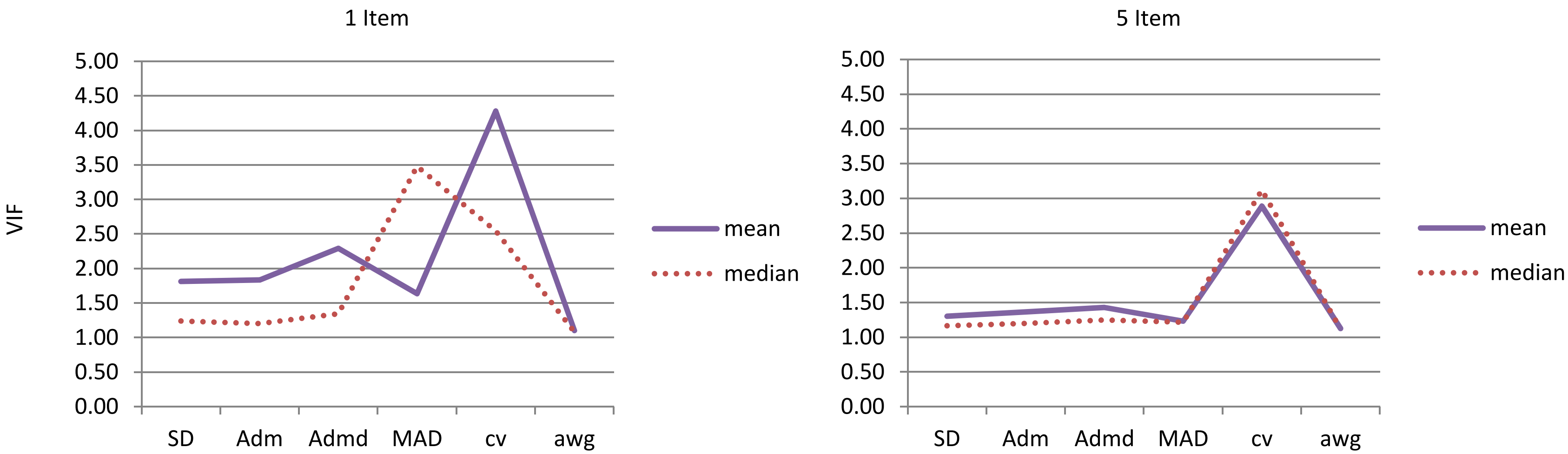
Figure 18 shows the three-way interaction between dispersion index, number of items and central tendency covariate on *VIF*. Figure 18 shows that the patterns of *VIF* look very different between the 1 and 5 item conditions.

*1 item context*. In the 1 item context there is a large difference in *VIF* between the mean and median covariate conditions for the *SD*, *ADm*, and *ADmd*, where the *VIF* is higher when controlling for the mean. For the *SD* and *ADm*, the average correlation when controlling for the mean is .67 and when controlling for the median the average correlation is .50. Contrary to what would be expected the *ADmd* VIF is higher than both the *SD* and the *ADm* when controlling for the mean. The average correlation between the *ADmd* and the mean in the 1 item context is .75 and when controlling for the median the average correlation is .50. The *VIF* for the *MAD* is comparatively lower when controlling for the mean (average correlation with the mean .62) but much higher when controlling for the median (correlation with the median .84). The *VIF* values for the *CV* suggest that the correlation between the *CV* and the mean in the 1 item context is .88 and the correlation between the *CV* and the median is .79. The *VIF* remains stable across the level covariates in the 1 item context.

*5 item context*. Compared to the 1 item context, the 5 item context *VIF* values are relatively stable across the dispersion indexes and between the mean and median covariate conditions. For the *SD* the average *VIF* when controlling for the mean is slightly higher than when controlling for the median. This small difference in *VIF*, however, corresponds to a correlation of .48 with the mean and .37 with the median. The *ADm* and *ADmd* display a similar pattern; the *VIF* is higher when the dispersion prediction model controls for the mean when compared to the median. Although the pattern is similar, the *VIF* values for the *ADm* and *ADmd* are slightly higher when compared to the *SD*. In the 5 item condition, the *VIF* for the *MAD* is consistent across the mean and median covariate conditions corresponding to a correlation of ~.42. Contrary to the 1 item condition, the VIF for the *CV* is smaller when controlling for the median.

The correlations are still high with both central tendency covariates however (~.81 for both conditions). Similar to the 1 item condition, the *VIF* values for the *awg* are stable and low across the mean and median covariate conditions.

Figure 18: Three-way interaction between dispersion index, number of items, and central tendency covariate on VIF




| | VIF, 1 Item | | VIF, 5 Item | |
|---|---|---|---|---|
| | mean | median | mean | median |
| SD | 1.81 (.67) | 1.24 (.44) | 1.30 (.48) | 1.16 (.37) |
| Adm | 1.83 (.67) | 1.20 (.41) | 1.36 (.51) | 1.20 (.41) |
| Admd | 2.29 (.75) | 1.34 (.50) | 1.43 (.55) | 1.25 (.45) |
| MAD | 1.63 (.62) | 3.48 (.84) | 1.23 (.43) | 1.22 (.42) |
| CV | 4.28 (.88) | 2.54 (.78) | 2.89 (.81) | 3.12 (.82) |
| awg | 1.10 (.30) | 1.08 (.27) | 1.13 (.34) | 1.12 (.33) |

Note: Correlation between dispersion index and central tendency covariate in parentheses

Figure 19 shows the three-way interaction between dispersion index, distribution shape, and central tendency covariate on *VIF*. For each of the dispersion indexes (except the *CV* and the *awg*) as the distribution moves from normal to heavy skewed there is an associated increase in *VIF* for both the mean and median conditions.

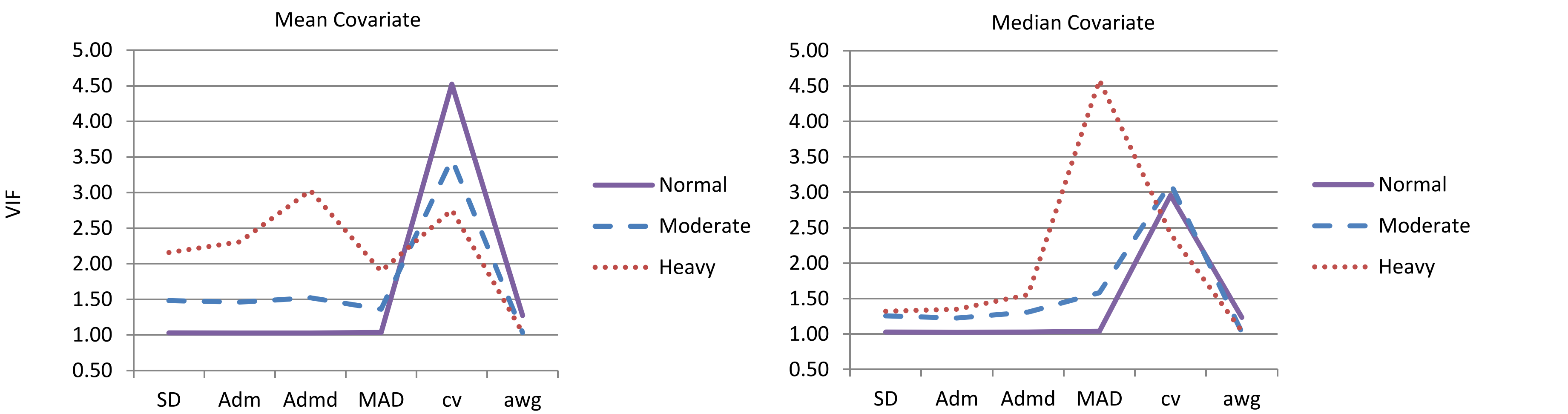
The patters displayed for the *SD* and the *ADm* across the levels of distribution shape and central tendency covariate are consistent. In the mean covariate condition the *VIF* for each of the *SD* and *ADm* dispersion indexes is low when the distribution shape is normal (correlation ~.15). In the moderately skewed, mean covariate condition the *VIF* increases significantly resulting in a correlation of ~.57 between each of the dispersion indexes and the mean. In the heavy skewed condition the *VIF* increases again resulting in a correlation of ~.74 between each of the dispersion indexes and the mean. When the *SD* and *ADmd* control for the median in the dispersion prediction model there is still an increase in *VIF* as the distribution moves from normal to heavy skewed, but the increase is smaller when compared to the mean covariate condition. The *VIF* is similar between the mean and median covariate normal distribution shape. In the moderately skewed distribution the *VIF* between the median and each of the dispersion indexes is slightly lower when compared to the mean (average correlation ~.44). In the heavy skewed distribution the *VIF* suggests an approximate .50 average correlation between the median and the *SD*/*ADm*. The pattern for the *ADmd* is similar to that of the *SD* and the *ADm* across the distribution shapes and central tendency covariate conditions. One noticeable difference is that there is a slight increase in *VIF* when the *ADmd* controls for the mean in the heavy skewed distribution resulting in an average correlation between the two at .82.

The *MAD* pattern of *VIF* among the levels of distribution skew in the mean covariate condition is similar to the *SD*/*ADm*/*ADmd* in that there is a systematic increase in *VIF* as the distribution moves from normal to heavy skew. The *VIF* values for the *MAD* when controlling for the mean are noticeably lower when compared to the *VIF* for the *SD*/*ADm*/*ADmd* resulting in a smaller average correlation between the *MAD* and the mean in dispersion prediction models. The pattern of *MAD VIF* in the median covariate condition is slightly higher but similar to the patterns for the *SD*/*ADm*/*ADmd* except for the heavy skewed condition. In the heavy skewed condition there was a substantial jump in correlation between the *MAD* and the median resulting in an approximate average correlation of greater than .88 in this condition.

The *VIF* for the *CV* decreases as the distribution moves from normal to heavy skewed. In the normal distribution, mean covariate condition the *VIF* for the *CV* is quite high resulting in an approximate average correlation of .88. In the moderate and heavy skewed distributions the *VIF* decreases and is still relatively high when compared to the other indexes. In median covariate condition the *VIF* for the *CV* fluctuates slightly (increase between the normal and moderate skew distributions; and decreases between the moderate and heavy skew distributions) but is steadily higher than the other indexes.

The *VIF* for the *awg* is relatively higher when compared to the *SD*/*ADm*/*ADmd*/*MAD* in the normal condition when both central tendency covariates are used. In the moderate and heavy skewed distributions, however, the *VIF* decreases and remains consistently and relatively lower across both skewed distributions and each of the central tendency covariate conditions.

Figure 19: Three-way interaction between dispersion index, distribution shape, and central tendency covariate on VIF




| | VIF, Mean Covariate | | | VIF, Median Covariate | | |
|---|---|---|---|---|---|---|
| | Normal | Moderate | Heavy | Normal | Moderate | Heavy |
| SD | 1.03 (.17) | 1.48 (.57) | 2.16 (.73) | 1.03 (.17) | 1.26 (.45) | 1.32 (.49) |
| Adm | 1.03 (.17) | 1.46 (.56) | 2.31 (.75) | 1.02 (.14) | 1.23 (.43) | 1.35 (.51) |
| Admd | 1.03 (.17) | 1.52 (.59) | 3.03 (.82) | 1.03 (.17) | 1.31 (.49) | 1.55 (.60) |
| MAD | 1.03 (.17) | 1.36 (.51) | 1.90 (.69) | 1.04 (.20) | 1.58 (.61) | 4.58 (.88) |
| CV | 4.52 (.88) | 3.47 (.84) | 2.75 (.80) | 2.96 (.81) | 3.12 (.82) | 2.41 (.76) |
| awg | 1.27 (.46) | 1.03 (.17) | 1.03 (.17) | 1.23 (.43) | 1.02 (.14) | 1.04 (.20) |

Note: Correlation between dispersion index and central tendency covariate in parentheses

Figure 20 shows the three-way interaction between dispersion index, distribution shape, and the number of items on *VIF*. In general, Figure 20 shows that across indexes and distribution shapes, the *VIF* inflation is more pronounced in the 1 item condition when compared to the 5 item condition.

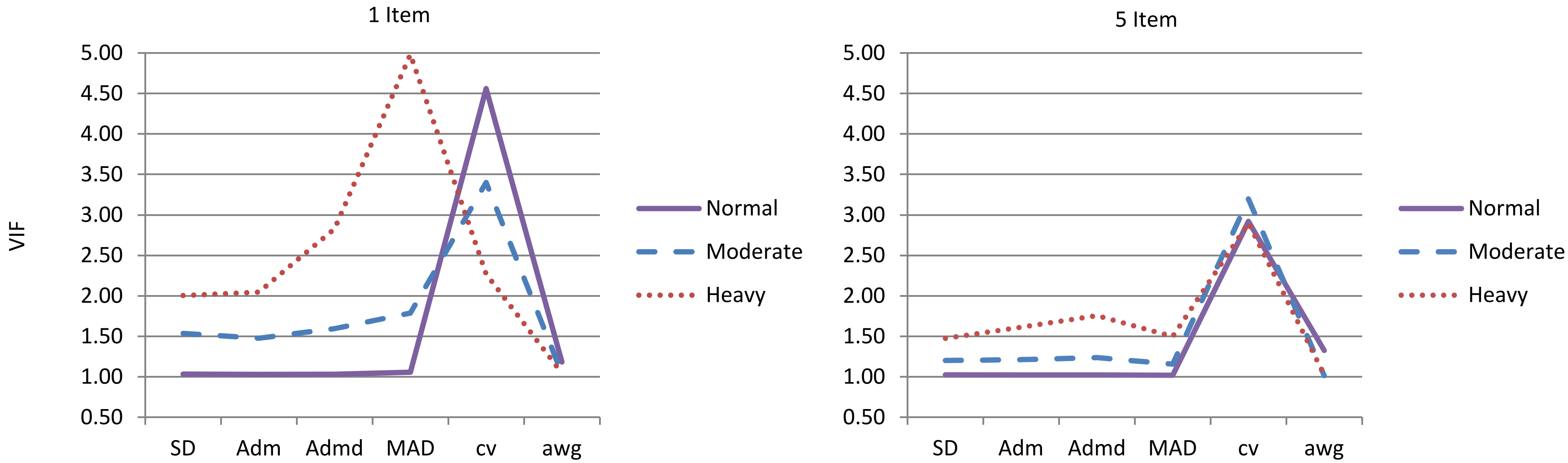
In the 1 and 5 item conditions the *VIF* pattern for the *SD* and *ADm* are very similar. In the 1 item condition, there is a steady increase in *VIF* for the *SD* and *ADm* as the distribution moves from normal to heavy skewed. In the 1 item condition, the *VIF* for the *ADmd* is comparable in the normal and moderate skewed conditions but is relatively higher in the heavy skewed condition (resulting in a correlation with the mean close to .80 in that condition). In the 5 item condition, the *VIF* for each of the *SD*, *ADm*, and the *ADmd* is consistent between the 1 and 5 item conditions in the normal distribution but the *VIF* is lower in the 5 item, moderate and heavy skewed conditions when compared to the 1 item context. To illustrate, in the moderate skewed distribution the *VIF* for the *SD* in the 5 item condition results in an average correlation of ~.41 (compared to an average correlation of ~.59 in the 1 item, moderately skewed distribution). In the heavy skewed condition the *VIF* for the SD in the 5 item condition results in an average correlation of ~.57 (compared to an average correlation of ~.71 in the 1 item, heavy skewed distribution). There is a similar reduction in relative average correlation for the *ADm* and the *ADmd* when comparing the *VIF* among the moderate and heavy skewed distributions between the 1 and 5 item contexts.

The VIF pattern for the *MAD* is generally consistent with the *SD*/*ADm*/*ADmd*. Within the 1 item context and 5 item contexts. In the 1 item context the *VIF* for the *MAD* is slightly higher than each of these other indexes, however. Further, in the 1 item, heavy skewed condition there is a significant increase in *VIF* between the *MAD* and the central tendency covariate (average correlation of .89).

The *VIF* for the *CV* continues to be very different from the *VIF* corresponding to the other indexes in the conditions reflected in Figure 20. In the 1 item context the *VIF* for the *CV* is greatest in the normal condition and decreases through the moderate and heavy skewed conditions. In the 1 item heavy skewed condition the *VIF* for the *CV* still results in a high average correlation with the central tendency covariate, .75. In the 5 item condition *VIF* for the *CV* was steady throughout the normal, moderate and heavy skew distributions and was substantially higher than the remaining indexes.

As in the previous effects, the *VIF* values for the *awg* shown in Figure 20 were relatively higher than the *SD*/*ADm*/*ADmd*/*MAD* in the normal 1 item and 5 item conditions. In the moderate and heavy skewed conditions the *VIF* for the *awg* decreased.

Figure 20: Three-way interaction between dispersion index, distribution shape, and number of items on VIF




| | VIF, 1 Item | | | VIF, 5 Item | | |
|---|---|---|---|---|---|---|
| | Normal | Moderate | Heavy | Normal | Moderate | Heavy |
| SD | 1.03 (.17) | 1.54 (.59) | 2.00 (.71) | 1.02 (.14) | 1.20 (.41) | 1.47 (.57) |
| Adm | 1.03 (.17) | 1.48 (.57) | 2.05 (.72) | 1.02 (.14) | 1.21 (.42) | 1.61 (.62) |
| Admd | 1.03 (.17) | 1.59 (.61) | 2.83 (.80) | 1.02 (.14) | 1.24 (.44) | 1.76 (.66) |
| MAD | 1.06 (.24) | 1.79 (.66) | 4.98 (.89) | 1.02 (.14) | 1.16 (.37) | 1.50 (.58) |
| CV | 4.56 (.88) | 3.40 (.84) | 2.27 (.75) | 2.92 (.81) | 3.20 (.83) | 2.90 (.81) |
| awg | 1.18 (.39) | 1.04 (.20) | 1.05 (.22) | 1.32 (.49) | 1.01 (.09) | 1.03 (.17) |

Note: Correlation between dispersion index and central tendency covariate in parentheses

# 5.0 DISCUSSION

Grounded in the results of previous simulation work (i.e., Roberson et al. 2007) and a history of poor performance, this study set out to explore the potential causes for poor performance and low power of dispersion prediction models in a polytomous item context. Specifically, the research questions were stated as follows:

1. Do the dispersion indexes present nonlinearity and / or heteroscedasticity in dispersion prediction multiple regression model in a polytomous item context?

2. To what extent does the correlation between the dispersion index and the level covariate in dispersion prediction multiple regression models impact their performance in a polytomous item context? More specifically, the questions are:
    2.1. Does the dispersion index computed from a skewed distribution affect the performance of the dispersion index in dispersion prediction model?
    2.2. Does the dispersion index computed from 5 polytomous items improve performance over those calculated from 1 polytomous item?

2.3. Does the use of median as the level covariate improve the performance of the dispersion index when compared to models that use the mean as the level covariate?

2.4. Is there difference among the dispersion index in their performance and is such difference dependent on the distribution shape, the number of items used to calculate the dispersion index, and the use of mean or median as the 'level' covariate?

The results of this study provide information necessary to begin answering these questions. First, the results of the study suggest that, regardless of the dispersion index used, dispersion prediction models do not systematically violate the regression assumptions of linearity and homoscedasticity. Second, the results suggest that distribution shape does influence the performance of dispersion prediction models through an increased correlation between the level and strength covariates in the multiple regression model. Third, the results suggest that the choice of dispersion index, the number of items used to derive the dispersion index, and the choice of central tendency covariate can all make a difference in dispersion prediction model performance by counteracting the negative influence of distributional skew on performance.

In section 5.1 through 5.4 the findings of the current study are discussed in terms of the practical research insight that can be offered to applied researchers as it relates to the stated research questions. The purpose each section is to present the factors that influence the performance of dispersion prediction models (good and bad) in a polytomous item context.

In the final section (5.5) the conclusions, limitations and directions for future research are discussed in three separate sections.

## 5.1 DISPERSION INDEX

The fundamental research question in the current study involved the potential for different dispersion indexes to perform differently in dispersion prediction multiple regression models across realistic study conditions. It was hypothesized that the distinct formulas corresponding to each of the dispersion indexes might result in performance differences. It was hypothesized that performance advantages for dispersion indexes may be realized through a reduced correlation with the central tendency covariate. Further, that performance differences may fluctuate depending on the shape of the distribution from which the dispersion index is computed, the central tendency covariate used (mean or median), and the number of items used to compute the dispersion index.

The results of this study suggest that the dispersion index choice can have a substantial impact on power and performance of dispersion prediction models in polytomous items. Based on the results of this study a few dispersion indexes performed somewhat equally well in polytomous items, while a few performed poorly. The best performing indexes (in terms of power, and $sr^2$, and Model $R^2$) were the *SD*, *ADm*, and the *ADmd*. The power advantages of the *SD*, *ADm,* and the *ADmd* are quite substantial over the *MAD*, *CV* and the *awg*. These advantages were evident across all of the conditions of the simulated data set and across the $sr^2$ and $R^2$ outcomes as well.

Of the three worst performing indexes, the *awg* performed the poorest. The *awg* displayed low power (and a corresponding small $sr^2$) across the levels of the simulated conditions (in the .10 effect size condition its average power was equal to .05; in the .30 effect size condition its average power was equal to .07; and in the .50 effect size condition its power was equal to .09). Based on the results, it appears as though the interpretability of the *awg* completely broke down in the 5 point response scale polytomous item context. These findings are not necessarily inconsistent with the theoretical behavior of the statistic in a 5 response scale, 1 and 5 item context. The *awg* statistic was originally intended for a distribution of significant scale such as performance and achievement tests (Brown & Hauenstien, 2005). Further, as cautioned by both Brown & Hauenstien (2005) and Golay et al. (2013) the performance and interpretability of the statistic deteriorates as the mean of the distribution approaches its end points. Consistently, a distribution of 5 discrete points that is moderately and/or heavily skewed can theoretically decrease the *awg's* performance. The descriptive statistics do indeed reflect this type of theoretical deterioration in performance. In the normal condition the power of the *awg* (albeit low when compared to the *SD*, *ADm*, and the *ADmd*) increases as the predefined dispersion index effect size increases and as the number of groups increases. However, there is no increase in the index's power in the moderate and heavy skewed distribution contexts. This is true of both the 1 item and 5 item contexts.

As discussed briefly, the *CV* displayed more power than the *MAD* and the *awg*, however it was still substantially lower than the *SD*, *ADm*, and the *ADmd* in most conditions (its average power in the .10 effect size was equal to .11; in the .30 condition, .23; and in the .50 condition, .38). The *CV* also had the highest Type I error and *VIF* values for the regression slope across the simulated conditions. Further, as the distributional skew increased, the Type I error for the *CV* increased substantially, while the Type I error for the other indexes increased less. Interestingly, distinct from all of the other measures, as the skew increased the *VIF* for the slope of the *CV* decreased. However, the *CV's VIF* value was still systematically larger than that of the other dispersion indexes. By dividing the sample standard deviation by the distribution mean, it was originally hypothesized that the formula restrictions of the *CV* would hinder its performance in discrete interval distributions, especially across skewed distributions. It was suspected that these issues could result in erratic and non-systematic performance of the static. The results of this study are consistent with the theoretical performance of the *CV*. Of all the dispersion indices, the *CV* performed the least predictably and systematically in the discrete interval distribution. These noticeable trends suggest that the *CV* is not a good dispersion index to use in the context of the current simulation (i.e., the polytomous item(s) with a 5 point response scale). Similar to the *awg*, the *CV* may be most appropriate for use in continuous distributions or those with a substantial scale between a lower and upper bound.

Distinct from the *CV* and *awg*, the performance of the *MAD* changed as expected across the conditions of the study (e.g., considering the levels of effect size and the number of aggregated observations), however it still displayed a lower relative power across the simulation parameters. The *MAD's* average power in the .10 condition was equal to .08; in the .30 condition, .21; and in the .50 condition, .36. As the effect size and number of groups increased, the power and $sr^2$ of the *MAD* also increased. The *MAD* also maintained acceptable levels of Type I error and *VIF* across the simulation conditions comparable to the other dispersion statistics.

Distinct from the poor performance of the *MAD*, *awg*, and *CV,* the *SD*, *ADm* and *ADmd* performed well across the levels of the simulation. These statistics showed much higher levels of power setting them apart as the best performing dispersion statistics to use in a 5 point polytomous item context. The performance of the *SD*, *ADm*, and *ADmd* was systematic and as expected across the levels of the simulated conditions suggesting that they perform well skewed distributions (where the mean approaches the distribution's end points) as well as normal ones (where the mean is close to the distribution's midpoint). Each of the indexes increased systematically in power, $sr^2$, and dispersion prediction model $R^2$ as the number of nested data points increased, the number of aggregated observations increased, and the effect size increased. It is also important to note that this study found greater power for dispersion prediction models than the study conducted by Roberson et al., (2007); especially when considering the performance of the *SD*, *ADm*, and *ADmd*. The practical differences in performance among the *SD*, *ADm*, and *ADmd* indexes are minimal in terms of statistical power, $sr^2$, and dispersion prediction model $R^2$. Therefore all may be suitable dispersion indexes for use in dispersion prediction models in polytomous item contexts.

## 5.2 DISTRIBUTION SHAPE AND VIF

The shape of the distribution was varied in the current study in order to determine if the performance of dispersion indexes varied as a result of distribution skew. Three reasons were originally hypothesized as to why dispersion indexes used in dispersion prediction models may be more or less susceptible to performance differences across distributional skew: 1) different dispersion indexes can be more or less robust in skewed distributions; 2) different dispersion indexes can perform differently as the mean approaches the distribution end-points; and 3) different dispersion indexes can more or less correlated with the average score of the distribution and these differences would become more apparent across the levels of distributional skew because skew naturally increases the relationship between the distribution mean and its variance.

The design of the current study makes it difficult to infer whether or not, and to what extent, the performance of the dispersion indexes fluctuated due to differences in robustness and formula limitations when the mean approached the end-points. Discussions regarding the differential patterns of performance for the index can be noted, however. The performance of the *SD*, *ADm*, *ADmd* gained power in the 1 item condition as the distribution skewed and little fluctuation among the levels of skew in the 5 item context. The systematic gains in power as the distribution skewed in the 1 item condition was most likely due to the median covariate condition. Distinct from the *SD*, *ADm*, and *ADmd*, the *MAD, CV*, and *awg* performed poorly across the levels of skew. As discussed above, the performance of the *awg* is not inconsistent with the theoretical nature of the statistic's formula. It appears as though the interpretability of the statistic deteriorated as the distribution skewed and the mean approached the endpoint of the 5 point response scale. The performance of the *MAD* and the *CV* was sporadic across the levels of skew. The power for the *CV* increased substantially through the levels of skew in the 1 item and the median covariate conditions, but decreased through the levels of skew in the 5 item and the mean covariate conditions (see Figure 7 Figure 8). Figure 7 Figure 8 also show that the *MAD* increased and decreased sporadically through the levels of skew between the 1 and 5 item conditions and the mean and median covariate conditions. As the sporadic performance of the *CV* and the *MAD* do not correspond precisely to *VIF* values, the performance differences for the *CV* and *MAD* are likely due to formula limitations for the indexes in polytomous items due to the interaction between distribution shape, number of items, and central tendency covariate.

The current study approached the mean by dispersion correlation as the most likely source of performance difference in dispersion indexes as a result of distribution skew. As such this suspected cause was explored more directly by computing the *VIF* for the dispersion regression coefficient and using it as an outcome in the mixed effects ANOVA. Using this approach, inferences could be made in terms of the patterns of performance and *VIF* among the conditions in the study.

Few of the dispersion indexes had resulting *VIF* values that consistently approached a value of 4. Only the *MAD*, *CV*, and *ADmd* had *VIF* values that exceeded 4 in some conditions. The *MAD* had the highest *VIF* value with the median, and the *ADmd* and *CV* with the mean. The *SD*, *ADm*, and *awg* maintained the lowest *VIF* values with the mean and/or median across the simulated conditions.

For the *SD*, *ADm*, *ADmd*, and *MAD* the *VIF* increased with distributional skew. This trend was expected and hypothesized. As the distribution became positively skewed the attrition of the upper half of the 5 point scale caused the mean and the dispersion to be positively correlated. Although there was some evidence that the power decreased with distributional skew (see Figure 12 and Figure 7), there is no significant main effect of skew on power (see Table 12). Skew impacted the power of the dispersion indexes primarily through its interaction with the central tendency covariate and number of items. For both of these interactions, higher levels of relative power corresponded to the condition with lower relative levels of *VIF*. Thus, the conditions which were able to reduce the correlation between the level and strength covariates in the dispersion prediction multiple regression model (i.e., controlling for the mean as opposed to the median and using 5 rather than 1 item to compute the dispersion index) seem to perform better through a reduced correlation. In other words, in conditions where there was a lower relative *VIF*, there is greater relative performance of the dispersion prediction models especially when using the *SD, ADm*, and *ADmd* dispersion indexes. This finding is consistent with the ideas presented throughout this study. Increasing the power of dispersion prediction models depends in part on reducing the correlation between the dispersion index and the level covariate.

## 5.3 NUMBER OF POLYTOMOUS ITEMS FROM WHICH THE DISPERSION CONSTRUCT IS DERIVED

Although, in the current study, the scale was fixed at 5 discrete points, the number of items was varied between 1 and 5 in order to create a condition in which variability between the same upper and lower bounds was relatively greater. The differences in dispersion model performance between these two contexts displayed one of the most practically significant differences of the study's conditions. The results suggest that there can be large gains in power in a multiple polytomous item context as opposed to using a single discrete scale. These gains are evident across all dispersion indexes used and all simulation conditions.

There are large discrepancies in *VIF* between the 1 and 5 item contexts. As such, the correlations between the dispersion indexes and the central tendency covariates are generally much higher in the 1 item context when compared to the 5 item condition. However, these performance advantages of the 5 item context are also evident in conditions of similar *VIF* between the 1 and 5 item contexts. To illustrate this, Figure 8 shows that the power for the 1 item condition in the normal distribution is substantially lower than that of the 5 item condition in the normal distribution, especially for the *SD*, *ADm*, and *ADmd*. Figure 20 shows that the *VIF* for both the 1 and 5 items conditions are similar. Thus, the power advantages for the 5 item composite condition are most likely due to the reduced correlation between the dispersion index and the central tendency covariate and more importantly, the increased variability of the dispersion index predictor as a result of its composite form.

There is a greater inflation of Type I error as the total sample size and predefined effect size increases in the single polytomous item context when compared to the 5 item context. Thus, in addition to the power benefits, the 5 item context may also provide the benefit of reduction in Type I error.

## 5.4 CENTRAL TENDENCY COVARIATE

As discussed, it is common practice within dispersion prediction model empirical studies to control for the mean of the distribution in the multiple regression equation (Cole et al., 2011; Bliese & Halverson, 1998). This is done because of the dependence that exists between the distribution level and its dispersion in a discrete distribution. Cole et al., (2011) argued that controlling for the level-effect of the distribution is crucial in order to ensure that a significant dispersion effect actually exists and is not a by-product of the level-effect.

Although it is common practice to control for the mean of the distribution, it was suggested that using the median as the level covariate in the dispersion prediction multiple regression model may increase the power of the dispersion index through a reduced correlation among the predictor variables. The results of the simulation suggest that there are significant and important performance differences between dispersion prediction models that use the mean and those that control for the median as the level covariate. The benefits of using the median as the level covariate exist only in the skewed distributions. In addition to the number of polytomous items (1 versus 5), the differences in dispersion model performance between the mean level covariate and median level covariate is one of the most practically significant differences in the study's conditions. These gains are most pronounced when the three best performing dispersion indexes are considered (i.e., the *SD*, *ADm*, and *ADmd*).

For the *SD*, *ADm*, and *ADmd*, using the median as the level covariate produces substantial gains in performance over the mean level covariate (up to 30% in heavy skewed distributions). As mentioned, the performance benefits of the median level covariate are only realized in the context of moderate and heavy skewed distributions. In the normally distributed context, there is no difference in performance. Consistent with the hypotheses of this study, the power differences appear to be a by-product of the reduced correlation between the dispersion index and the level covariate in the dispersion prediction multiple regression model. In the normal distribution the VIF for the slope of the dispersion construct regression coefficient for the best performing indexes (i.e., the *SD*, *ADm*, and *ADmd*) is consistent and low. As the distribution shape moves to moderate and heavily skewed, the *VIF* increases more dramatically when controlling for the mean than when controlling for the median. Interestingly, although there are no real benefits in using a median-based estimator of scale and controlling for the mean, there appears to be a noticeable benefit when using a mean or median based estimators of scale and controlling for the median.

These benefits of controlling for the median in the skewed distributions are noticeable in both the one and five item contexts. Importantly, however, there is an inflation of Type I error when using the median level covariate as the distribution becomes skewed. This inflation is very pronounced in the 1 item context. Considering the *SD*/*ADm*/*ADmd*, in the moderately skewed distribution, 1 item condition the Type I error begins to rise around the 60 aggregated observations of 100 nested data points (6000 total sample size) and continues to rise slowly as the total sample size increases. In the same condition there is greater increase in the very large sample size conditions (400 observations with 100 nested data points-a total sample size of 40,000). For the *SD*/*ADm*/*ADm*, in the heavy skewed, 1 item condition the inflation of Type I error when controlling for the median begins at a much lower sample size; those commonly encountered in dispersion prediction model studies. Thus, the power advantages seen in the 1 item context may be a by-product of the Type I error inflation in this context.

In the five item, moderate skew condition, however, the inflation of Type I error is minimal for all of the dispersion indexes. For the *SD*/*ADm*/*ADmd* in the 5 item, heavy skew condition, the inflation of Type I error is slightly elevated at the 120 aggregated observation/30 nested data point condition (~.09) and slowly increases to a maximum Type I error rate of .17 for the *SD* and ~.20 for both the *ADm*/*ADmd* in the 40,000 total sample size condition. Because the median covariate advantages are evident across all the levels of sample size, effect size, and both moderate and heavy skew (see tables corresponding to power for each cell in the design in Appendix C), however, there are likely power advantages in controlling for the median in skewed distributions that cannot be explained by the inflation of Type I error in this context.

## 5.5 CONCLUSIONS, LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

### 5.5.1 Conclusions

The current simulation extended the previous simulation conducted by Roberson et al. (2007) in multiple ways. First the distribution shape was varied between normal, moderate skew, and heavy skew. Second, up to 400 aggregated data points were included as opposed to 120. Third, median based estimators of scale were included (i.e., the *MAD*, and the *ADmd*). Fourth, a 5 point response scale polytomous item was used as opposed to a seven point response scale. Fifth, both the mean and the median were used as the central tendency covariate in the dispersion prediction multiple regression model. Sixth, the number of polytomous items from which the dispersion construct was derived was varied between 1 and 5 as opposed to a single item. Finally, the focus of the current simulation was to explore the reasons for low power of the dispersion construct in the dispersion prediction multiple regression models and as such less emphasis was placed on the level and strength x level effects.

Overall the sample standard deviation (*SD*), the average deviation around the mean (*ADm*), and the average deviation around the median (*ADmd*) are the recommendable dispersion statistics in the 5 point response scale polytomous item context. Through this study it was found that computing the *SD*, *ADm*, and *ADmd* from multiple polytomous items provides the most power and the highest $sr^2$ for the effect of the dispersion construct on the generated outcome. Overall, when the distribution of nested data points is normal, there is no difference between dispersion prediction model performance when controlling for the mean versus the median. When the distribution of nested data points is skewed, however, the best performing dispersion prediction models compute the *SD*, *ADm*, or *ADmd* from multiple items and the median is used as the level covariate.

The current study found much higher levels of power for the dispersion construct in dispersion prediction models when compared to the Roberson et al., 2007 simulation. Under certain conditions (i.e., a large effect size exists and the number of aggregated observations is substantial) the power for the dispersion construct can achieve the desired level of 80%. Through this study it was found that the most important factors that contribute to the performance of dispersion prediction models in the 5 point polyomous item context are: 1) the dispersion index used; 2) the number of items used to compute the dispersion index; and 3) the shape of the distribution from which the dispersion construct is computed combined with the level covariate chosen.

It is important to note, however, although the current study found greater power for dispersion prediction models than the study conducted by Roberson et al., (2007), the power revealed in the 5 point response scale context of the current study suggests that the power, for even the best performing indexes, was lower than expected.

Table **13** and Table **14** show the highest power obtained among all the indexes in the normal, mean covariate condition as well as the expected power for the dispersion effect. Where the dispersion indexes were computed from a single polytomous item, the observed power was consistently and substantially lower than the expected power. For example, for a large effect (effect size = .50) with 30 observations, the expected power was .81 while the observed highest power was only .22. The 5 item context displayed relatively higher power values when compared to the 1 item condition, but the power was still consistently lower than the expected power across the levels of effect size and number of aggregated observations. The observed power in the 5 item context was able to achieve the expected power only in the .50 effect size, with greater than 120 aggregated observation/30 nested data point conditions.

Given these large discrepancies between observed and expected power, the pervasiveness of disconfirmed hypotheses in organizational studies resulting from the execution of dispersion prediction multiple regression models may be attributable more to methodological issues rather than the underlying group dispersion theories. Although the current study attempted to identify creative ways to improve the performance of dispersion prediction models across distributional shapes, additional potential sources for low power in polytomous items should continue to be examined.

Table 13: Observed versus Expected Power in the 1 Item Condition

| Effect Size | Number of Aggregated Observations | Highest power obtained (15 nested data points) | Highest power obtained (30 nested data points) | Expected Power for the Dispersion Effect |
|---|---|---|---|---|
| .10 | 30 | .05 | .06 | .08 |
| | 60 | .07 | .06 | .12 |
| | 120 | .07 | .07 | .19 |
| | 400 | .11 | .17 | .52 |
| .30 | 30 | .08 | .11 | .36 |
| | 60 | .12 | .17 | .65 |
| | 120 | .19 | .31 | .92 |
| | 400 | .52 | .77 | >.99 |
| .50 | 30 | .08 | .22 | .81 |
| | 60 | .22 | .41 | .99 |
| | 120 | .47 | .72 | >.99 |
| | 400 | .94 | .99 | >.99 |

Note: Obtained power values correspond to the normal distribution, mean covariate condition. Expected power values computed using SAS 9.3.

Table 14: Observed versus Expected Power in the 5 Item Condition

| Effect Size | Number of Aggregated Observations | Highest power obtained (15 nested data points) | Highest power obtained (30 nested data points) | Expected Power for the Dispersion Effect |
|---|---|---|---|---|
| .10 | 30 | .06 | .06 | .08 |
| | 60 | .07 | .08 | .12 |
| | 120 | .08 | .12 | .19 |
| | 400 | .21 | .30 | .52 |
| .30 | 30 | .13 | .19 | .36 |
| | 60 | .26 | .36 | .65 |
| | 120 | .45 | .63 | .92 |
| | 400 | .91 | .98 | >.99 |
| .50 | 30 | .13 | .47 | .81 |
| | 60 | .57 | .81 | .99 |
| | 120 | .86 | >.99 | >.99 |
| | 400 | >.99 | >.99 | >.99 |

Note: Obtained power values correspond to the normal distribution, mean covariate condition. Expected power values computed using SAS 9.3.

### 5.5.2 Limitations and directions for future research

The limitations of the study and suggestions for future dispersion prediction model research need to be noted. First the results of this study should only be interpreted as generalizable to polytomous items with five discrete points. In this context it was found that the *MAD*, *CV*, and *awg* are not desirable dispersion indexes. The performance of these indexes still needs to be assessed in a continuous distribution context as many real world studies have found the *CV* and *awg* to perform better than the *SD* in this context. Extending the simulation to a continuous context would allow the performance of the *awg* and the *CV* to be further assessed. It could be determined if the *awg* truly breaks down in the bounded polytomous item context. It could also be determined if, and under what conditions, the sporadic and nonsystematic performance of the *CV* improves in a continuous setting. Further, the data generation algorithm incorporated the *SD* into the generation of the group level outcome. Thus, as a result of the data generation method, the performance assessment across the dispersion indexes may favor the *SD* (as well as those measures highly correlated with it). In order to further investigate the relative performance of the dispersion indexes studied in the current simulation, the data generation algorithm could be varied in future studies. Future studies may also supplement the simulation with real world data to further explore the performance of these dispersion indexes in dispersion prediction multiple regression models.

Second, it is unclear why as to why there is an inflation of Type I error as the number of observations increases, especially within the 1 item, heavy skew context when the median is used as the level covariate. The inflated Type I error was not because of violation of linearity and homoscedasticity in dispersion prediction models as there was no evidence for such violation.

The possible reason could be the misspecification with the median used as the level covariate while the mean was used in the data generation model. Roberson et al.'s (2007) simulation reported an inflation of Type I error for the mean possibly due to model misspecification when the interaction term omitted from the multiple regression equation but included in the data generation algorithm. Future studies might focus on the causes and conditions under which an inflation of Type I error is an issue for the dispersion effect.

It would be interesting to determine if increasing the scale of the distribution (i.e., the number of discrete scale points in the polytomous item) would provide any benefit to the statistical precision and power of dispersion prediction models in a polytomous item context. The current study fixed the number of scale points to five. Future studies may vary the number of response scale points from 5 (as was used in the current study) to 9 or 11 to see if any added benefit would exist. The results of this simulation suggest that increasing the variability of the predictor (i.e., by using the average of 5 polytomous items as opposed to 1 polytomous item) increases the performance of the of dispersion prediction models overall. Thus, introducing additional variance may increase performance even more. These hypotheses, however, are subject to testing in future studies.

This study focused on the performance of dispersion prediction models, with the primary interest in being able to detect a significant dispersion effect when the effect was present. Future simulations may also be interested in determining how the distribution shape, and dispersion index chosen (if applicable), impacts the power of the mean. Interestingly, although differences in power and $sr^2$ of the dispersion indexes were found across the levels of the simulation, the $R^2$ remained steady. It is possible that changes in distribution shape and choice of the dispersion index decreases the power of the mean. These ideas could be extended to the median as well.

## APPENDIX A: Distribution of simulated 1 and 5 polytomous items

Figure 21: Shape of Distribution of Item 1 and Item Average for normally distributed 5-point scale

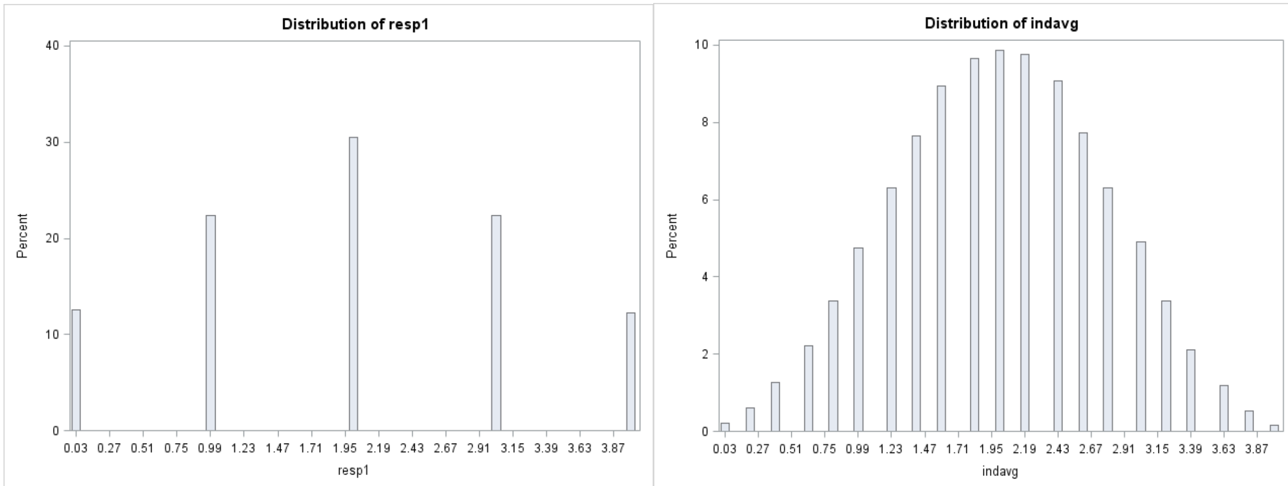
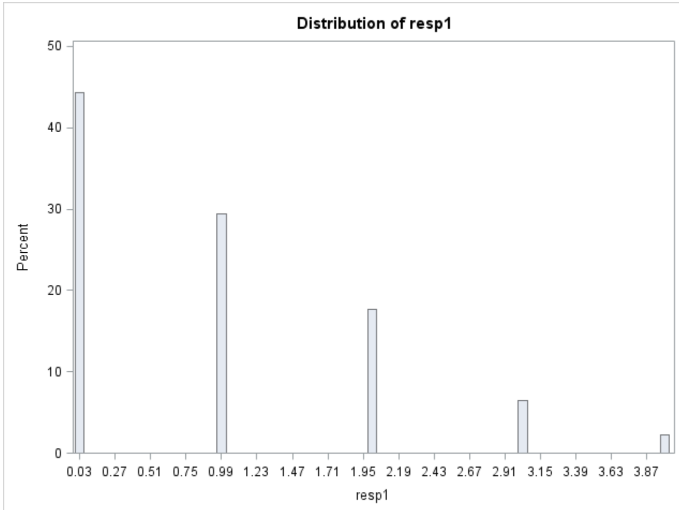


Figure 22: Shape of Distribution of Item 1 and Item Average for moderately skewed 5-point scale



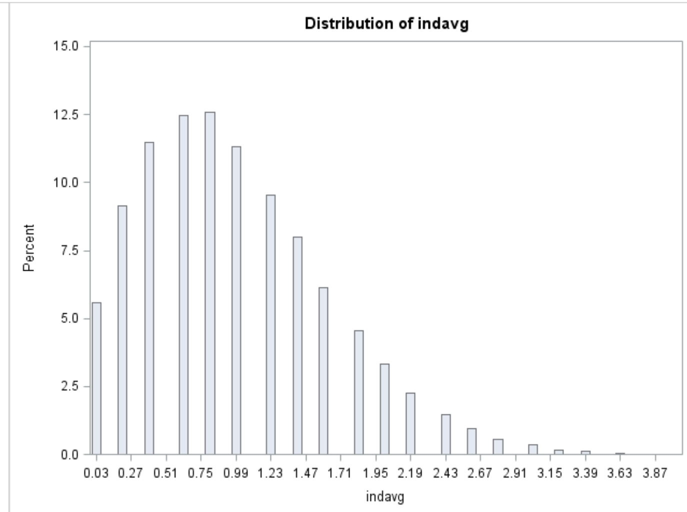
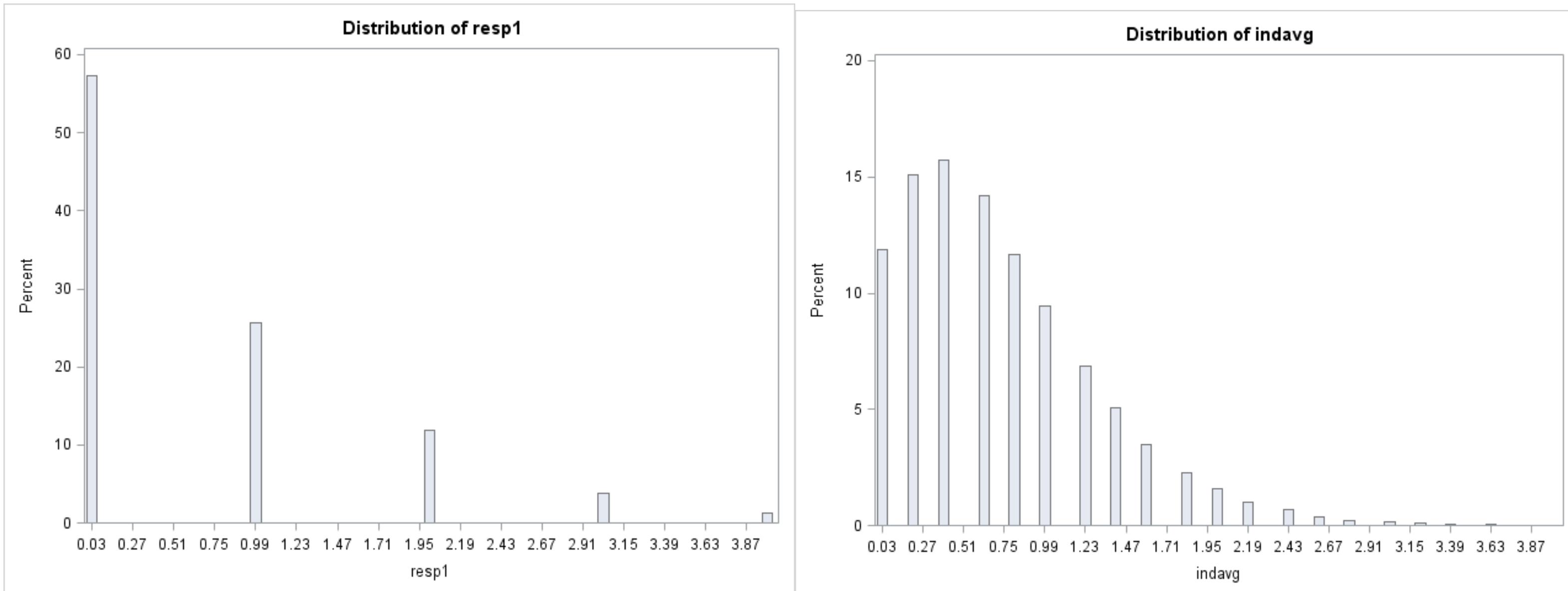



Figure 23: Shape of distribution of item 1 and item average for heavy skewed 5-point scale



# APPENDIX B: Type I error for each condition

## Type 1 Error

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | adm | admd | MAD | CV | awg | SD | adm | admd | MAD | CV | awg | SD | adm | admd | MAD | CV | awg | SD | adm | admd | MAD | CV | awg |
| Normal | 30 | 15 | .06 | .06 | .06 | .05 | .06 | .06 | .06 | .06 | .06 | .05 | .08 | .06 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .05 | .04 | .04 | .04 | .05 |
| | | 30 | .05 | .04 | .05 | .05 | .05 | .05 | .05 | .05 | .05 | .05 | .07 | .05 | .06 | .06 | .06 | .06 | .05 | .06 | .06 | .05 | .05 | .06 | .06 | .06 |
| | | 100 | .05 | .05 | .04 | .05 | .04 | .05 | .05 | .04 | .04 | .06 | .08 | .05 | .05 | .05 | .05 | .06 | .05 | .05 | .05 | .05 | .05 | .06 | .05 | .04 |
| | 60 | 15 | .05 | .04 | .05 | .05 | .05 | .04 | .05 | .05 | .04 | .05 | .08 | .05 | .05 | .05 | .05 | .04 | .06 | .06 | .04 | .05 | .04 | .04 | .05 | .05 |
| | | 30 | .05 | .05 | .04 | .06 | .06 | .06 | .05 | .04 | .04 | .05 | .11 | .06 | .06 | .05 | .05 | .06 | .04 | .05 | .06 | .05 | .06 | .06 | .06 | .05 |
| | | 100 | .06 | .06 | .06 | .04 | .06 | .06 | .05 | .06 | .06 | .03 | .14 | .06 | .05 | .05 | .05 | .05 | .05 | .06 | .05 | .04 | .04 | .05 | .05 | .05 |
| | 120 | 15 | .05 | .05 | .05 | .05 | .06 | .06 | .05 | .06 | .05 | .04 | .10 | .07 | .06 | .06 | .06 | .07 | .06 | .04 | .06 | .06 | .06 | .06 | .07 | .05 |
| | | 30 | .05 | .05 | .06 | .06 | .05 | .06 | .06 | .05 | .06 | .06 | .12 | .06 | .05 | .04 | .05 | .04 | .05 | .06 | .05 | .05 | .05 | .04 | .05 | .06 |
| | | 100 | .05 | .06 | .06 | .04 | .05 | .05 | .05 | .05 | .06 | .04 | .18 | .05 | .05 | .06 | .06 | .05 | .05 | .05 | .05 | .06 | .06 | .05 | .05 | .05 |
| | 400 | 15 | .05 | .05 | .05 | .05 | .04 | .06 | .05 | .05 | .05 | .05 | .27 | .05 | .05 | .05 | .05 | .06 | .05 | .05 | .04 | .04 | .05 | .06 | .09 | .05 |
| | | 30 | .06 | .05 | .05 | .05 | .05 | .04 | .05 | .06 | .05 | .05 | .30 | .05 | .04 | .04 | .04 | .04 | .04 | .05 | .04 | .04 | .04 | .04 | .05 | .04 |
| | | 100 | .04 | .05 | .05 | .05 | .06 | .05 | .05 | .05 | .05 | .05 | .51 | .05 | .04 | .04 | .04 | .06 | .04 | .05 | .04 | .04 | .04 | .05 | .05 | .05 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moderate Skew | 30 | 15 | .05 | .05 | .05 | .06 | .06 | .06 | .06 | .05 | .05 | .05 | .06 | .06 | .06 | .05 | .06 | .06 | .06 | .06 | .06 | .06 | .06 | .06 | .06 | .06 |
| | | 30 | .06 | .05 | .04 | .05 | .07 | .05 | .06 | .06 | .05 | .05 | .07 | .05 | .05 | .05 | .04 | .06 | .06 | .04 | .05 | .05 | .05 | .06 | .05 | .05 |
| | | 100 | .06 | .05 | .05 | .04 | .05 | .05 | .07 | .07 | .06 | .04 | .08 | .06 | .06 | .05 | .06 | .05 | .04 | .05 | .05 | .05 | .05 | .05 | .05 | .04 |
| | 60 | 15 | .05 | .05 | .04 | .04 | .04 | .05 | .07 | .07 | .07 | .04 | .08 | .06 | .05 | .05 | .05 | .05 | .06 | .05 | .07 | .07 | .06 | .05 | .07 | .04 |
| | | 30 | .05 | .05 | .04 | .04 | .04 | .04 | .06 | .06 | .06 | .05 | .09 | .04 | .04 | .04 | .04 | .05 | .04 | .04 | .05 | .04 | .05 | .05 | .05 | .04 |
| | | 100 | .06 | .05 | .05 | .06 | .06 | .04 | .08 | .10 | .08 | .05 | .13 | .04 | .05 | .05 | .05 | .05 | .06 | .04 | .05 | .06 | .05 | .05 | .06 | .05 |
| | 120 | 15 | .05 | .05 | .05 | .04 | .06 | .04 | .09 | .08 | .08 | .05 | .13 | .05 | .06 | .05 | .05 | .05 | .07 | .07 | .07 | .06 | .06 | .06 | .08 | .06 |
| | | 30 | .03 | .04 | .05 | .05 | .06 | .05 | .09 | .10 | .08 | .05 | .13 | .05 | .06 | .05 | .05 | .06 | .05 | .06 | .06 | .07 | .06 | .06 | .06 | .05 |
| | | 100 | .05 | .06 | .05 | .06 | .07 | .05 | .11 | .14 | .12 | .05 | .18 | .05 | .05 | .04 | .04 | .05 | .05 | .05 | .05 | .05 | .05 | .05 | .05 | .05 |
| | 400 | 15 | .05 | .06 | .05 | .06 | .11 | .06 | .16 | .16 | .16 | .06 | .33 | .08 | .04 | .05 | .05 | .04 | .08 | .06 | .06 | .07 | .06 | .04 | .08 | .06 |
| | | 30 | .05 | .04 | .05 | .06 | .10 | .06 | .19 | .22 | .19 | .05 | .32 | .07 | .06 | .05 | .05 | .06 | .10 | .07 | .08 | .07 | .07 | .06 | .09 | .06 |
| | | 100 | .06 | .07 | .07 | .06 | .10 | .06 | .29 | .37 | .28 | .05 | .50 | .08 | .05 | .06 | .06 | .05 | .09 | .05 | .09 | .10 | .10 | .06 | .09 | .05 |
| Heavy Skew | 30 | 15 | .04 | .04 | .05 | .06 | .08 | .06 | .06 | .07 | .08 | .05 | .10 | .06 | .04 | .05 | .05 | .05 | .05 | .05 | .04 | .05 | .04 | .04 | .05 | .05 |
| | | 30 | .04 | .04 | .05 | .06 | .06 | .04 | .09 | .10 | .10 | .05 | .10 | .04 | .05 | .05 | .06 | .06 | .05 | .05 | .05 | .05 | .06 | .05 | .05 | .05 |
| | | 100 | .05 | .05 | .06 | .07 | .05 | .05 | .10 | .11 | .12 | .05 | .11 | .04 | .05 | .04 | .04 | .04 | .05 | .06 | .06 | .05 | .05 | .05 | .05 | .06 |
| | 60 | 15 | .05 | .04 | .04 | .05 | .06 | .06 | .08 | .10 | .10 | .05 | .12 | .06 | .05 | .05 | .05 | .04 | .06 | .06 | .05 | .05 | .05 | .04 | .05 | .06 |
| | | 30 | .04 | .03 | .04 | .05 | .06 | .05 | .11 | .14 | .14 | .05 | .15 | .05 | .05 | .05 | .05 | .06 | .06 | .05 | .06 | .07 | .06 | .06 | .05 | .04 |
| | | 100 | .07 | .07 | .09 | .05 | .07 | .06 | .19 | .21 | .23 | .05 | .20 | .06 | .07 | .06 | .06 | .07 | .07 | .05 | .08 | .09 | .09 | .07 | .06 | .05 |
| | 120 | 15 | .05 | .04 | .04 | .05 | .09 | .06 | .13 | .17 | .18 | .04 | .20 | .06 | .05 | .06 | .05 | .06 | .08 | .07 | .06 | .06 | .07 | .05 | .07 | .07 |
| | | 30 | .06 | .05 | .06 | .05 | .08 | .05 | .20 | .25 | .26 | .05 | .25 | .05 | .07 | .07 | .06 | .06 | .07 | .04 | .09 | .10 | .09 | .06 | .07 | .04 |
| | | 100 | .06 | .07 | .08 | .04 | .07 | .05 | .32 | .38 | .40 | .06 | .34 | .05 | .06 | .06 | .06 | .04 | .07 | .06 | .09 | .09 | .10 | .05 | .07 | .06 |
| | 400 | 15 | .06 | .05 | .06 | .04 | .14 | .05 | .37 | .48 | .51 | .03 | .56 | .05 | .07 | .07 | .06 | .06 | .16 | .06 | .10 | .11 | .11 | .06 | .12 | .06 |
| | | 30 | .05 | .06 | .09 | .05 | .16 | .05 | .56 | .68 | .72 | .05 | .69 | .04 | .06 | .07 | .07 | .06 | .15 | .05 | .15 | .16 | .15 | .07 | .11 | .06 |
| | | 100 | .09 | .11 | .20 | .06 | .20 | .04 | .79 | .86 | .89 | .05 | .81 | .04 | .06 | .07 | .06 | .06 | .17 | .06 | .17 | .21 | .22 | .09 | .18 | .06 |

## APPENDIX C: Power for each condition

### Power, Effect Size = .10

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .05 | .04 | .04 | .05 | .06 | .05 | .05 | .04 | .04 | .06 | .07 | .06 | .06 | .06 | .06 | .05 | .06 | .06 | .07 | .06 | .07 | .05 | .06 | .06 |
| | | 30 | .05 | .06 | .05 | .05 | .05 | .05 | .04 | .05 | .04 | .05 | .05 | .05 | .05 | .05 | .05 | .06 | .05 | .05 | .06 | .06 | .05 | .06 | .05 | .05 |
| | | 100 | .05 | .06 | .05 | .03 | .04 | .04 | .06 | .06 | .05 | .03 | .07 | .05 | .07 | .06 | .06 | .06 | .06 | .05 | .07 | .06 | .07 | .06 | .06 | .05 |
| | 60 | 15 | .07 | .08 | .07 | .04 | .05 | .05 | .07 | .07 | .07 | .04 | .05 | .05 | .07 | .07 | .07 | .05 | .06 | .06 | .07 | .06 | .07 | .06 | .05 | .06 |
| | | 30 | .05 | .04 | .05 | .06 | .05 | .05 | .05 | .05 | .05 | .06 | .07 | .06 | .08 | .08 | .07 | .06 | .07 | .06 | .08 | .07 | .07 | .06 | .06 | .06 |
| | | 100 | .08 | .07 | .08 | .04 | .07 | .05 | .09 | .08 | .08 | .04 | .11 | .06 | .10 | .10 | .10 | .08 | .10 | .06 | .11 | .11 | .11 | .08 | .08 | .06 |
| | 120 | 15 | .07 | .07 | .06 | .05 | .06 | .04 | .07 | .07 | .06 | .05 | .10 | .04 | .08 | .09 | .08 | .06 | .07 | .05 | .09 | .08 | .09 | .05 | .06 | .05 |
| | | 30 | .07 | .06 | .07 | .05 | .05 | .05 | .07 | .07 | .07 | .05 | .10 | .05 | .12 | .12 | .11 | .09 | .10 | .05 | .12 | .12 | .11 | .09 | .08 | .05 |
| | | 100 | .09 | .11 | .10 | .06 | .06 | .04 | .10 | .10 | .10 | .06 | .16 | .05 | .15 | .16 | .16 | .09 | .11 | .05 | .15 | .15 | .15 | .09 | .09 | .05 |
| | 400 | 15 | .11 | .11 | .11 | .07 | .05 | .04 | .10 | .10 | .10 | .06 | .22 | .05 | .21 | .18 | .18 | .11 | .14 | .05 | .20 | .18 | .18 | .10 | .07 | .06 |
| | | 30 | .17 | .15 | .15 | .08 | .06 | .06 | .16 | .15 | .14 | .08 | .23 | .05 | .30 | .27 | .27 | .16 | .19 | .06 | .30 | .28 | .27 | .15 | .12 | .06 |
| | | 100 | .26 | .25 | .24 | .07 | .06 | .04 | .26 | .24 | .24 | .07 | .37 | .05 | .43 | .42 | .42 | .24 | .31 | .06 | .43 | .42 | .41 | .25 | .22 | .06 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moderate Skew | 30 | 15 | .06 | .06 | .06 | .06 | .05 | .05 | .08 | .08 | .08 | .06 | .07 | .06 | .06 | .06 | .06 | .06 | .05 | .04 | .07 | .07 | .06 | .06 | .05 | .05 |
| | | 30 | .06 | .07 | .07 | .06 | .05 | .05 | .08 | .08 | .09 | .06 | .08 | .06 | .06 | .06 | .06 | .06 | .05 | .05 | .08 | .08 | .07 | .06 | .05 | .05 |
| | | 100 | .06 | .07 | .07 | .06 | .05 | .05 | .08 | .09 | .09 | .06 | .08 | .04 | .07 | .07 | .07 | .06 | .04 | .06 | .09 | .08 | .08 | .07 | .05 | .06 |
| | 60 | 15 | .06 | .06 | .05 | .04 | .06 | .05 | .09 | .09 | .10 | .05 | .11 | .06 | .06 | .05 | .05 | .05 | .04 | .05 | .08 | .07 | .07 | .05 | .05 | .05 |
| | | 30 | .06 | .07 | .08 | .06 | .06 | .06 | .12 | .12 | .11 | .05 | .11 | .07 | .09 | .09 | .10 | .06 | .05 | .05 | .11 | .11 | .11 | .06 | .04 | .05 |
| | | 100 | .07 | .08 | .07 | .06 | .07 | .06 | .14 | .15 | .13 | .06 | .16 | .06 | .10 | .10 | .10 | .08 | .06 | .06 | .13 | .13 | .13 | .09 | .06 | .06 |
| | 120 | 15 | .06 | .06 | .06 | .06 | .07 | .05 | .15 | .15 | .14 | .05 | .15 | .06 | .07 | .08 | .08 | .08 | .05 | .05 | .13 | .12 | .12 | .08 | .05 | .05 |
| | | 30 | .07 | .06 | .08 | .08 | .07 | .05 | .17 | .17 | .17 | .06 | .14 | .06 | .11 | .11 | .10 | .07 | .06 | .04 | .16 | .16 | .15 | .08 | .04 | .05 |
| | | 100 | .12 | .13 | .12 | .06 | .08 | .04 | .29 | .29 | .26 | .06 | .23 | .05 | .14 | .15 | .14 | .09 | .07 | .05 | .20 | .20 | .20 | .10 | .06 | .05 |
| | 400 | 15 | .07 | .07 | .10 | .08 | .11 | .07 | .37 | .37 | .35 | .08 | .36 | .10 | .13 | .12 | .12 | .07 | .05 | .04 | .33 | .30 | .28 | .09 | .06 | .04 |
| | | 30 | .16 | .17 | .19 | .13 | .13 | .06 | .48 | .52 | .50 | .10 | .40 | .10 | .27 | .27 | .27 | .17 | .08 | .04 | .45 | .46 | .45 | .20 | .08 | .04 |
| | | 100 | .34 | .35 | .31 | .17 | .12 | .05 | .72 | .76 | .69 | .13 | .55 | .08 | .47 | .47 | .46 | .22 | .12 | .05 | .65 | .63 | .63 | .27 | .10 | .05 |
| Heavy Skew | 30 | 15 | .06 | .06 | .06 | .05 | .05 | .05 | .11 | .12 | .11 | .04 | .10 | .05 | .07 | .07 | .06 | .05 | .07 | .05 | .08 | .08 | .08 | .05 | .07 | .06 |
| | | 30 | .05 | .06 | .07 | .06 | .06 | .05 | .10 | .12 | .11 | .05 | .11 | .04 | .07 | .06 | .07 | .06 | .05 | .04 | .07 | .08 | .08 | .06 | .05 | .05 |
| | | 100 | .07 | .08 | .08 | .05 | .06 | .05 | .15 | .17 | .17 | .05 | .14 | .04 | .07 | .07 | .07 | .07 | .05 | .05 | .09 | .10 | .10 | .07 | .06 | .05 |
| | 60 | 15 | .04 | .04 | .04 | .07 | .07 | .07 | .10 | .13 | .14 | .05 | .13 | .07 | .06 | .07 | .06 | .05 | .07 | .05 | .09 | .09 | .09 | .06 | .06 | .05 |
| | | 30 | .06 | .07 | .07 | .04 | .07 | .06 | .17 | .21 | .22 | .05 | .20 | .05 | .07 | .08 | .08 | .06 | .05 | .05 | .12 | .12 | .13 | .06 | .05 | .05 |
| | | 100 | .09 | .10 | .12 | .05 | .08 | .06 | .28 | .30 | .30 | .05 | .26 | .06 | .11 | .11 | .12 | .07 | .06 | .05 | .15 | .16 | .17 | .08 | .06 | .05 |
| | 120 | 15 | .05 | .06 | .06 | .05 | .08 | .05 | .21 | .26 | .27 | .06 | .25 | .05 | .05 | .06 | .07 | .06 | .06 | .06 | .13 | .15 | .14 | .06 | .05 | .06 |
| | | 30 | .08 | .10 | .13 | .04 | .12 | .06 | .33 | .39 | .40 | .05 | .34 | .05 | .09 | .09 | .10 | .07 | .04 | .05 | .17 | .20 | .19 | .09 | .05 | .05 |
| | | 100 | .17 | .18 | .19 | .06 | .12 | .05 | .56 | .59 | .60 | .06 | .46 | .04 | .18 | .19 | .19 | .09 | .05 | .05 | .29 | .31 | .31 | .12 | .05 | .05 |
| | 400 | 15 | .07 | .09 | .11 | .05 | .19 | .07 | .56 | .68 | .70 | .05 | .67 | .06 | .10 | .10 | .11 | .07 | .06 | .05 | .35 | .36 | .34 | .11 | .05 | .05 |
| | | 30 | .13 | .21 | .29 | .06 | .27 | .06 | .80 | .89 | .89 | .06 | .78 | .05 | .20 | .21 | .23 | .13 | .06 | .05 | .52 | .55 | .55 | .18 | .06 | .05 |
| | | 100 | .42 | .48 | .54 | .06 | .30 | .06 | .97 | .98 | .99 | .07 | .93 | .05 | .47 | .50 | .52 | .22 | .05 | .05 | .76 | .79 | .79 | .33 | .07 | .05 |

## Power, Effect Size = .30

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | ested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .08 | .08 | .08 | .05 | .06 | .05 | .08 | .08 | .07 | .05 | .05 | .05 | .13 | .12 | .12 | .09 | .11 | .08 | .13 | .12 | .12 | .09 | .10 | .07 |
| | | 30 | .11 | .10 | .10 | .05 | .06 | .05 | .11 | .10 | .10 | .05 | .05 | .06 | .19 | .18 | .18 | .11 | .15 | .08 | .19 | .17 | .18 | .11 | .14 | .08 |
| | | 100 | .16 | .14 | .14 | .05 | .06 | .06 | .16 | .14 | .14 | .06 | .06 | .07 | .28 | .27 | .28 | .13 | .23 | .11 | .29 | .28 | .28 | .14 | .20 | .10 |
| | 60 | 15 | .12 | .12 | .12 | .08 | .07 | .06 | .11 | .11 | .13 | .08 | .06 | .07 | .26 | .24 | .23 | .13 | .18 | .09 | .26 | .24 | .23 | .13 | .13 | .08 |
| | | 30 | .17 | .16 | .15 | .05 | .07 | .05 | .16 | .16 | .16 | .06 | .06 | .06 | .36 | .33 | .33 | .19 | .27 | .11 | .36 | .34 | .33 | .19 | .23 | .10 |
| | | 100 | .30 | .27 | .28 | .05 | .07 | .05 | .31 | .27 | .27 | .05 | .09 | .06 | .54 | .52 | .52 | .25 | .40 | .10 | .53 | .52 | .52 | .25 | .35 | .10 |
| | 120 | 15 | .18 | .19 | .18 | .09 | .08 | .05 | .18 | .19 | .19 | .09 | .08 | .04 | .45 | .43 | .42 | .22 | .33 | .11 | .45 | .42 | .43 | .22 | .24 | .09 |
| | | 30 | .31 | .28 | .29 | .08 | .08 | .06 | .31 | .28 | .28 | .08 | .06 | .06 | .63 | .57 | .58 | .34 | .46 | .12 | .62 | .57 | .57 | .33 | .36 | .10 |
| | | 100 | .58 | .53 | .54 | .06 | .11 | .05 | .57 | .53 | .53 | .06 | .10 | .05 | .84 | .83 | .83 | .46 | .69 | .12 | .84 | .83 | .83 | .46 | .62 | .11 |
| | 400 | 15 | .52 | .49 | .49 | .18 | .07 | .09 | .51 | .47 | .48 | .17 | .17 | .08 | .91 | .90 | .90 | .56 | .73 | .12 | .92 | .90 | .90 | .56 | .53 | .10 |
| | | 30 | .77 | .71 | .72 | .19 | .11 | .06 | .77 | .70 | .71 | .19 | .15 | .07 | .98 | .98 | .98 | .83 | .91 | .11 | .98 | .98 | .98 | .83 | .85 | .10 |
| | | 100 | .98 | .96 | .96 | .14 | .16 | .05 | .98 | .96 | .96 | .14 | .28 | .05 | .00 | .00 | .00 | .93 | .99 | .13 | .00 | .00 | .00 | .94 | .98 | .12 |
| Moderate Skew | 30 | 15 | .07 | .08 | .08 | .05 | .05 | .06 | .11 | .13 | .13 | .05 | .08 | .06 | .11 | .11 | .10 | .08 | .06 | .05 | .14 | .13 | .13 | .08 | .06 | .06 |
| | | 30 | .09 | .09 | .09 | .08 | .05 | .04 | .13 | .13 | .12 | .07 | .06 | .05 | .16 | .14 | .15 | .09 | .10 | .05 | .18 | .18 | .17 | .10 | .09 | .05 |
| | | 100 | .19 | .17 | .17 | .08 | .06 | .06 | .24 | .24 | .23 | .08 | .11 | .05 | .29 | .29 | .29 | .14 | .16 | .06 | .32 | .32 | .32 | .17 | .13 | .06 |
| | 60 | 15 | .12 | .13 | .15 | .07 | .05 | .06 | .22 | .21 | .22 | .08 | .10 | .07 | .22 | .20 | .20 | .10 | .10 | .06 | .28 | .26 | .25 | .11 | .10 | .07 |
| | | 30 | .16 | .16 | .17 | .07 | .06 | .06 | .26 | .26 | .27 | .08 | .12 | .06 | .32 | .30 | .30 | .15 | .13 | .05 | .40 | .36 | .36 | .18 | .13 | .05 |
| | | 100 | .32 | .30 | .29 | .10 | .07 | .06 | .46 | .45 | .41 | .12 | .17 | .06 | .53 | .52 | .51 | .22 | .24 | .05 | .60 | .59 | .59 | .25 | .18 | .06 |
| | 120 | 15 | .16 | .17 | .18 | .10 | .09 | .05 | .33 | .34 | .34 | .12 | .19 | .07 | .36 | .33 | .33 | .13 | .16 | .05 | .49 | .46 | .44 | .15 | .13 | .05 |
| | | 30 | .29 | .30 | .30 | .13 | .08 | .05 | .50 | .50 | .49 | .14 | .22 | .07 | .58 | .54 | .55 | .28 | .21 | .05 | .69 | .66 | .65 | .31 | .18 | .06 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 100 | .57 | .55 | .52 | .14 | .08 | .06 | .73 | .74 | .70 | .16 | .26 | .06 | .84 | .83 | .82 | .38 | .46 | .05 | .89 | .88 | .88 | .43 | .34 | .06 |
| | 400 | 15 | .41 | .43 | .49 | .23 | .18 | .09 | .79 | .82 | .82 | .24 | .51 | .13 | .83 | .78 | .77 | .43 | .31 | .05 | .94 | .92 | .92 | .50 | .26 | .05 |
| | | 30 | .73 | .74 | .78 | .37 | .19 | .07 | .95 | .95 | .95 | .39 | .55 | .11 | .97 | .97 | .96 | .74 | .58 | .04 | .99 | .99 | .99 | .81 | .49 | .05 |
| | | 100 | .98 | .98 | .97 | .45 | .21 | .07 | .00 | .00 | .00 | .50 | .73 | .10 | .00 | .00 | .00 | .89 | .88 | .06 | .00 | .00 | .00 | .93 | .79 | .06 |
| Heavy Skew | 30 | 15 | .06 | .08 | .08 | .06 | .07 | .06 | .12 | .14 | .15 | .04 | .13 | .06 | .10 | .09 | .10 | .06 | .06 | .05 | .14 | .14 | .14 | .07 | .06 | .05 |
| | | 30 | .10 | .10 | .10 | .06 | .06 | .07 | .19 | .20 | .21 | .05 | .14 | .07 | .12 | .13 | .13 | .07 | .06 | .05 | .17 | .18 | .18 | .08 | .06 | .06 |
| | | 100 | .19 | .19 | .17 | .08 | .09 | .05 | .34 | .33 | .32 | .06 | .22 | .05 | .25 | .25 | .25 | .11 | .10 | .07 | .31 | .31 | .31 | .13 | .06 | .07 |
| | 60 | 15 | .08 | .10 | .11 | .04 | .10 | .06 | .23 | .26 | .29 | .05 | .24 | .06 | .15 | .14 | .14 | .07 | .05 | .06 | .23 | .23 | .22 | .09 | .05 | .07 |
| | | 30 | .16 | .19 | .18 | .07 | .09 | .06 | .38 | .42 | .42 | .06 | .30 | .05 | .28 | .26 | .26 | .11 | .07 | .07 | .35 | .35 | .34 | .14 | .07 | .08 |
| | | 100 | .32 | .33 | .31 | .08 | .14 | .06 | .63 | .61 | .59 | .05 | .40 | .05 | .48 | .49 | .49 | .17 | .11 | .06 | .60 | .61 | .61 | .23 | .08 | .06 |
| | 120 | 15 | .11 | .16 | .18 | .04 | .12 | .06 | .37 | .44 | .47 | .06 | .35 | .05 | .24 | .24 | .24 | .10 | .07 | .06 | .43 | .43 | .42 | .14 | .06 | .06 |
| | | 30 | .25 | .32 | .35 | .06 | .19 | .07 | .63 | .70 | .71 | .06 | .53 | .06 | .47 | .45 | .45 | .17 | .10 | .06 | .64 | .64 | .64 | .23 | .08 | .06 |
| | | 100 | .57 | .57 | .54 | .09 | .23 | .05 | .88 | .88 | .88 | .05 | .68 | .04 | .81 | .80 | .81 | .32 | .18 | .05 | .90 | .89 | .89 | .45 | .09 | .06 |
| | 400 | 15 | .35 | .47 | .51 | .06 | .34 | .10 | .88 | .93 | .93 | .09 | .85 | .08 | .67 | .66 | .67 | .24 | .11 | .05 | .91 | .91 | .90 | .34 | .09 | .05 |
| | | 30 | .70 | .81 | .82 | .07 | .45 | .11 | .99 | .00 | .99 | .13 | .95 | .09 | .95 | .96 | .96 | .48 | .21 | .05 | .99 | .00 | .99 | .66 | .15 | .06 |
| | | 100 | .98 | .98 | .98 | .19 | .60 | .09 | .00 | .00 | .00 | .10 | .99 | .06 | .00 | .00 | .00 | .80 | .42 | .07 | .00 | .00 | .00 | .90 | .17 | .07 |

## Power, Effect Size = .50

| | | | 1 Item | | | | | | | | | | | | 5 Item | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .08 | .08 | .08 | .05 | .06 | .05 | .08 | .08 | .07 | .05 | .05 | .05 | .13 | .12 | .12 | .09 | .11 | .08 | .13 | .12 | .12 | .09 | .10 | .07 |
| | | 30 | .22 | .20 | .20 | .07 | .08 | .05 | .21 | .19 | .19 | .07 | .06 | .05 | .47 | .44 | .43 | .23 | .34 | .15 | .46 | .44 | .43 | .23 | .29 | .15 |
| | | 100 | .43 | .38 | .38 | .06 | .09 | .06 | .41 | .36 | .37 | .05 | .06 | .07 | .70 | .67 | .67 | .34 | .56 | .20 | .69 | .67 | .67 | .34 | .49 | .19 |
| | 60 | 15 | .22 | .21 | .20 | .09 | .07 | .06 | .22 | .20 | .20 | .09 | .05 | .06 | .57 | .53 | .53 | .26 | .40 | .15 | .58 | .52 | .52 | .28 | .31 | .14 |
| | | 30 | .41 | .37 | .36 | .10 | .08 | .06 | .40 | .37 | .36 | .10 | .06 | .06 | .81 | .78 | .78 | .46 | .62 | .17 | .81 | .78 | .77 | .46 | .54 | .17 |
| | | 100 | .72 | .66 | .66 | .07 | .16 | .05 | .70 | .65 | .65 | .06 | .07 | .06 | .95 | .94 | .94 | .62 | .87 | .25 | .95 | .95 | .94 | .61 | .83 | .24 |
| | 120 | 15 | .47 | .42 | .44 | .17 | .10 | .09 | .45 | .41 | .43 | .17 | .07 | .09 | .86 | .85 | .84 | .48 | .70 | .19 | .86 | .84 | .83 | .47 | .58 | .17 |
| | | 30 | .72 | .67 | .68 | .19 | .11 | .07 | .71 | .67 | .67 | .19 | .08 | .08 | .98 | .97 | .97 | .79 | .91 | .22 | .98 | .97 | .97 | .79 | .84 | .21 |
| | | 100 | .96 | .93 | .94 | .11 | .21 | .08 | .95 | .93 | .94 | .11 | .07 | .09 | .00 | .00 | .00 | .90 | .99 | .23 | .00 | .00 | .00 | .90 | .98 | .23 |
| | 400 | 15 | .94 | .92 | .93 | .42 | .14 | .15 | .93 | .91 | .92 | .40 | .12 | .13 | .00 | .00 | .00 | .96 | .00 | .25 | .00 | .00 | .00 | .96 | .98 | .23 |
| | | 30 | .99 | .99 | .99 | .45 | .22 | .09 | .99 | .99 | .99 | .45 | .09 | .09 | .00 | .00 | .00 | .00 | .00 | .21 | .00 | .00 | .00 | .00 | .00 | .21 |
| | | 100 | .00 | .00 | .00 | .27 | .36 | .07 | .00 | .00 | .00 | .26 | .15 | .08 | .00 | .00 | .00 | .00 | .00 | .21 | .00 | .00 | .00 | .00 | .00 | .21 |
| Moderate Skew | 30 | 15 | .12 | .12 | .14 | .07 | .07 | .05 | .17 | .16 | .18 | .07 | .09 | .06 | .26 | .24 | .23 | .12 | .12 | .05 | .31 | .29 | .29 | .13 | .11 | .05 |
| | | 30 | .21 | .20 | .21 | .09 | .05 | .06 | .27 | .26 | .27 | .11 | .08 | .06 | .45 | .41 | .41 | .19 | .21 | .05 | .49 | .46 | .46 | .21 | .19 | .06 |
| | | 100 | .40 | .38 | .37 | .10 | .08 | .05 | .48 | .44 | .43 | .13 | .13 | .05 | .68 | .67 | .66 | .26 | .40 | .05 | .72 | .70 | .70 | .28 | .33 | .06 |
| | 60 | 15 | .22 | .23 | .23 | .10 | .08 | .07 | .32 | .33 | .34 | .11 | .15 | .07 | .48 | .46 | .45 | .20 | .22 | .05 | .57 | .55 | .53 | .22 | .18 | .05 |
| | | 30 | .37 | .37 | .39 | .16 | .09 | .07 | .50 | .49 | .51 | .18 | .14 | .07 | .74 | .71 | .70 | .37 | .35 | .06 | .80 | .78 | .77 | .40 | .27 | .06 |
| | | 100 | .69 | .67 | .62 | .17 | .08 | .06 | .77 | .74 | .71 | .21 | .17 | .07 | .93 | .93 | .93 | .49 | .64 | .05 | .95 | .95 | .95 | .54 | .55 | .06 |
| | 120 | 15 | .39 | .40 | .41 | .16 | .12 | .08 | .59 | .59 | .61 | .18 | .25 | .10 | .77 | .73 | .74 | .33 | .35 | .06 | .86 | .83 | .81 | .37 | .30 | .07 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 30 | .71 | .70 | .73 | .27 | .13 | .07 | .83 | .84 | .84 | .33 | .32 | .09 | .97 | .97 | .97 | .66 | .61 | .07 | .99 | .98 | .98 | .72 | .54 | .07 |
| | | 100 | .96 | .94 | .93 | .30 | .13 | .06 | .98 | .98 | .98 | .38 | .37 | .07 | .00 | .00 | .00 | .78 | .85 | .07 | .00 | .00 | .00 | .83 | .76 | .08 |
| | 400 | 15 | .89 | .89 | .92 | .43 | .25 | .14 | .98 | .99 | .99 | .53 | .66 | .23 | .00 | .00 | .00 | .86 | .85 | .05 | .00 | .00 | .00 | .90 | .76 | .05 |
| | | 30 | .99 | .99 | .00 | .71 | .32 | .14 | .00 | .00 | .00 | .78 | .74 | .23 | .00 | .00 | .00 | .99 | .98 | .05 | .00 | .00 | .00 | .99 | .94 | .06 |
| | | 100 | .00 | .00 | .00 | .79 | .36 | .11 | .00 | .00 | .00 | .90 | .87 | .15 | .00 | .00 | .00 | .00 | .00 | .07 | .00 | .00 | .00 | .00 | .99 | .07 |
| Heavy Skew | 30 | 15 | .11 | .12 | .13 | .05 | .07 | .05 | .20 | .22 | .23 | .06 | .14 | .06 | .19 | .18 | .18 | .09 | .08 | .06 | .24 | .24 | .24 | .11 | .07 | .07 |
| | | 30 | .18 | .21 | .22 | .08 | .09 | .07 | .32 | .35 | .35 | .07 | .22 | .06 | .32 | .33 | .33 | .11 | .10 | .07 | .40 | .40 | .41 | .14 | .09 | .08 |
| | | 100 | .38 | .36 | .30 | .11 | .10 | .06 | .56 | .55 | .52 | .05 | .31 | .06 | .64 | .63 | .62 | .19 | .22 | .07 | .70 | .70 | .70 | .25 | .15 | .07 |
| | 60 | 15 | .15 | .19 | .20 | .07 | .11 | .06 | .34 | .38 | .39 | .05 | .26 | .05 | .34 | .32 | .33 | .11 | .10 | .06 | .47 | .46 | .46 | .14 | .10 | .06 |
| | | 30 | .35 | .44 | .41 | .06 | .16 | .06 | .62 | .67 | .65 | .08 | .44 | .06 | .64 | .62 | .62 | .23 | .16 | .07 | .75 | .73 | .74 | .30 | .12 | .08 |
| | | 100 | .69 | .68 | .59 | .13 | .18 | .08 | .85 | .85 | .82 | .04 | .54 | .06 | .92 | .90 | .90 | .35 | .34 | .08 | .95 | .94 | .94 | .47 | .20 | .08 |
| | 120 | 15 | .31 | .38 | .38 | .05 | .17 | .06 | .60 | .66 | .68 | .07 | .46 | .06 | .64 | .63 | .63 | .21 | .14 | .06 | .80 | .78 | .78 | .28 | .10 | .06 |
| | | 30 | .63 | .71 | .68 | .11 | .28 | .07 | .89 | .92 | .91 | .09 | .71 | .06 | .92 | .91 | .92 | .38 | .28 | .09 | .96 | .96 | .96 | .52 | .20 | .09 |
| | | 100 | .95 | .94 | .89 | .21 | .35 | .10 | .99 | .99 | .99 | .06 | .86 | .08 | .00 | .00 | .00 | .67 | .52 | .08 | .00 | .00 | .00 | .81 | .30 | .09 |
| | 400 | 15 | .79 | .89 | .89 | .06 | .44 | .13 | .99 | .99 | .00 | .17 | .95 | .08 | .99 | .99 | .00 | .57 | .41 | .06 | .00 | .00 | .00 | .75 | .29 | .06 |
| | | 30 | .99 | .00 | .00 | .16 | .72 | .17 | .00 | .00 | .00 | .21 | .00 | .12 | .00 | .00 | .00 | .86 | .67 | .07 | .00 | .00 | .00 | .97 | .46 | .07 |
| | | 100 | .00 | .00 | .00 | .49 | .85 | .15 | .00 | .00 | .00 | .14 | .00 | .10 | .00 | .00 | .00 | .99 | .93 | .10 | .00 | .00 | .00 | .00 | .61 | .10 |

## APPENDIX D: $sr^2$ for each condition

### $sr^2$, Effect Size = .10

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | ested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .03 | .03 | .03 | .03 | .03 | .04 | .03 | .03 | .03 | .03 | .04 | .04 | .04 | .04 | .04 | .03 | .04 | .04 | .04 | .04 | .04 | .03 | .03 | .03 |
| | | 30 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 | .03 |
| | | 100 | .04 | .04 | .03 | .03 | .03 | .03 | .04 | .04 | .04 | .03 | .04 | .03 | .04 | .04 | .04 | .03 | .03 | .03 | .04 | .04 | .04 | .03 | .03 | .03 |
| | 60 | 15 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 |
| | | 30 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 |
| | | 100 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 |
| | 120 | 15 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 |
| | | 30 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 |
| | | 100 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 |
| | 400 | 15 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .01 | .00 | .01 | .00 | .00 | .00 | .00 | .00 | .01 | .00 | .00 | .00 | .00 | .00 |
| | | 30 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .01 | .00 | .01 | .01 | .01 | .00 | .01 | .00 | .01 | .01 | .01 | .00 | .00 | .00 |
| | | 100 | .01 | .01 | .01 | .00 | .00 | .00 | .01 | .01 | .01 | .00 | .01 | .00 | .01 | .01 | .01 | .01 | .01 | .00 | .01 | .01 | .01 | .01 | .01 | .00 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moderate Skew | 30 | 15 | .04 | .04 | .04 | .04 | .04 | .03 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .03 | .04 | .04 | .04 | .04 | .04 | .03 |
| | | 30 | .04 | .04 | .04 | .04 | .03 | .03 | .04 | .05 | .05 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .03 | .03 | .04 | .04 | .04 | .04 | .03 | .03 |
| | | 100 | .04 | .04 | .04 | .04 | .03 | .03 | .04 | .05 | .04 | .03 | .04 | .03 | .04 | .04 | .04 | .04 | .03 | .03 | .04 | .04 | .04 | .04 | .03 | .03 |
| | 60 | 15 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 |
| | | 30 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .03 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 |
| | | 100 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .03 | .03 | .02 | .03 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .03 | .03 | .02 | .02 | .02 |
| | 120 | 15 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .02 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 |
| | | 30 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .01 | .01 | .01 | .01 |
| | | 100 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .02 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .01 | .01 |
| | 400 | 15 | .00 | .00 | .00 | .00 | .00 | .00 | .01 | .01 | .01 | .00 | .01 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .01 | .01 | .01 | .00 | .00 | .00 |
| | | 30 | .00 | .00 | .01 | .00 | .00 | .00 | .01 | .01 | .01 | .00 | .01 | .00 | .01 | .01 | .01 | .00 | .00 | .00 | .01 | .01 | .01 | .01 | .00 | .00 |
| | | 100 | .01 | .01 | .01 | .00 | .00 | .00 | .02 | .02 | .02 | .00 | .01 | .00 | .01 | .01 | .01 | .01 | .00 | .00 | .01 | .01 | .01 | .01 | .00 | .00 |
| Heavy Skew | 30 | 15 | .04 | .04 | .04 | .04 | .04 | .03 | .05 | .05 | .05 | .04 | .05 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 | .04 |
| | | 30 | .03 | .04 | .04 | .03 | .04 | .03 | .05 | .05 | .05 | .04 | .05 | .03 | .04 | .04 | .04 | .03 | .03 | .03 | .04 | .04 | .04 | .04 | .03 | .03 |
| | | 100 | .04 | .04 | .04 | .03 | .04 | .03 | .06 | .06 | .06 | .03 | .06 | .03 | .04 | .04 | .04 | .04 | .03 | .03 | .04 | .04 | .04 | .04 | .03 | .03 |
| | 60 | 15 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .03 | .03 | .02 | .03 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 |
| | | 30 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .04 | .04 | .02 | .04 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .03 | .02 | .02 | .02 |
| | | 100 | .02 | .02 | .03 | .02 | .02 | .02 | .05 | .05 | .05 | .02 | .04 | .02 | .02 | .02 | .02 | .02 | .02 | .02 | .03 | .03 | .03 | .02 | .02 | .02 |
| | 120 | 15 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .02 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .01 |
| | | 30 | .01 | .01 | .01 | .01 | .01 | .01 | .03 | .03 | .03 | .01 | .03 | .01 | .01 | .01 | .01 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .01 | .01 |
| | | 100 | .02 | .02 | .02 | .01 | .01 | .01 | .04 | .05 | .05 | .01 | .03 | .01 | .02 | .02 | .02 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .01 | .01 |
| | 400 | 15 | .00 | .00 | .00 | .00 | .01 | .00 | .01 | .02 | .02 | .00 | .02 | .00 | .00 | .00 | .00 | .00 | .00 | .00 | .01 | .01 | .01 | .00 | .00 | .00 |
| | | 30 | .00 | .01 | .01 | .00 | .01 | .00 | .02 | .03 | .03 | .00 | .02 | .00 | .01 | .01 | .01 | .00 | .00 | .00 | .01 | .01 | .01 | .01 | .00 | .00 |
| | | 100 | .01 | .01 | .01 | .00 | .01 | .00 | .04 | .04 | .04 | .00 | .03 | .00 | .01 | .01 | .01 | .01 | .00 | .00 | .02 | .02 | .02 | .01 | .00 | .00 |

## $sr^2$, Effect Size = .30

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .04 | .04 | .04 | .03 | .03 | .03 | .04 | .04 | .04 | .03 | .03 | .03 | .06 | .05 | .05 | .04 | .05 | .04 | .06 | .05 | .05 | .04 | .04 | .04 |
| | | 30 | .05 | .04 | .04 | .03 | .04 | .03 | .05 | .04 | .04 | .03 | .03 | .03 | .07 | .07 | .07 | .05 | .06 | .04 | .07 | .06 | .06 | .05 | .05 | .04 |
| | | 100 | .06 | .06 | .06 | .03 | .04 | .03 | .06 | .06 | .06 | .03 | .04 | .04 | .09 | .09 | .09 | .06 | .07 | .05 | .09 | .09 | .09 | .06 | .07 | .05 |
| | 60 | 15 | .03 | .02 | .03 | .02 | .02 | .02 | .03 | .02 | .03 | .02 | .02 | .02 | .04 | .04 | .04 | .03 | .03 | .02 | .04 | .04 | .04 | .03 | .03 | .02 |
| | | 30 | .03 | .03 | .03 | .02 | .02 | .02 | .03 | .03 | .03 | .02 | .02 | .02 | .05 | .05 | .05 | .03 | .04 | .02 | .05 | .05 | .05 | .03 | .04 | .02 |
| | | 100 | .05 | .04 | .04 | .02 | .02 | .02 | .05 | .04 | .04 | .02 | .02 | .02 | .08 | .07 | .07 | .04 | .06 | .02 | .08 | .07 | .07 | .04 | .05 | .02 |
| | 120 | 15 | .02 | .02 | .02 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .01 | .01 | .03 | .03 | .03 | .02 | .03 | .01 | .03 | .03 | .03 | .02 | .02 | .01 |
| | | 30 | .02 | .02 | .02 | .01 | .01 | .01 | .02 | .02 | .02 | .01 | .01 | .01 | .05 | .04 | .04 | .03 | .03 | .01 | .05 | .04 | .04 | .03 | .03 | .01 |
| | | 100 | .04 | .04 | .04 | .01 | .01 | .01 | .04 | .04 | .04 | .01 | .01 | .01 | .07 | .07 | .07 | .03 | .05 | .01 | .07 | .07 | .07 | .03 | .05 | .01 |
| | 400 | 15 | .01 | .01 | .01 | .00 | .00 | .00 | .01 | .01 | .01 | .00 | .00 | .00 | .03 | .03 | .03 | .01 | .02 | .00 | .03 | .03 | .03 | .01 | .01 | .00 |
| | | 30 | .02 | .02 | .02 | .01 | .00 | .00 | .02 | .02 | .02 | .01 | .00 | .00 | .04 | .04 | .04 | .02 | .03 | .00 | .04 | .04 | .04 | .02 | .02 | .00 |
| | | 100 | .04 | .03 | .03 | .00 | .00 | .00 | .04 | .03 | .03 | .00 | .01 | .00 | .07 | .06 | .06 | .03 | .05 | .00 | .07 | .06 | .06 | .03 | .04 | .00 |
| Moderate Skew | 30 | 15 | .04 | .05 | .04 | .04 | .04 | .04 | .05 | .06 | .06 | .04 | .04 | .04 | .05 | .05 | .05 | .04 | .04 | .04 | .06 | .06 | .06 | .04 | .04 | .04 |
| | | 30 | .04 | .04 | .05 | .04 | .03 | .03 | .06 | .06 | .06 | .04 | .04 | .04 | .06 | .06 | .06 | .05 | .05 | .03 | .07 | .07 | .07 | .05 | .04 | .03 |
| | | 100 | .07 | .06 | .06 | .04 | .04 | .03 | .08 | .08 | .08 | .04 | .05 | .03 | .09 | .09 | .09 | .05 | .06 | .04 | .10 | .10 | .10 | .06 | .05 | .04 |
| | 60 | 15 | .03 | .03 | .03 | .02 | .02 | .02 | .04 | .04 | .04 | .02 | .03 | .02 | .04 | .04 | .04 | .02 | .02 | .02 | .05 | .05 | .04 | .03 | .02 | .02 |
| | | 30 | .03 | .03 | .03 | .02 | .02 | .02 | .04 | .05 | .04 | .02 | .03 | .02 | .05 | .05 | .05 | .03 | .03 | .02 | .06 | .06 | .06 | .03 | .03 | .02 |
| | | 100 | .05 | .05 | .05 | .02 | .02 | .02 | .07 | .07 | .06 | .03 | .03 | .02 | .07 | .07 | .07 | .04 | .04 | .02 | .09 | .08 | .08 | .04 | .03 | .02 |
| | 120 | 15 | .02 | .02 | .02 | .01 | .01 | .01 | .03 | .03 | .03 | .01 | .02 | .01 | .03 | .03 | .03 | .02 | .02 | .01 | .04 | .04 | .04 | .02 | .01 | .01 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 30 | .02 | .02 | .03 | .01 | .01 | .01 | .04 | .04 | .04 | .01 | .02 | .01 | .04 | .04 | .04 | .02 | .02 | .01 | .05 | .05 | .05 | .02 | .02 | .01 |
| | | 100 | .04 | .04 | .04 | .01 | .01 | .01 | .06 | .06 | .05 | .02 | .02 | .01 | .07 | .07 | .07 | .03 | .03 | .01 | .08 | .08 | .08 | .03 | .03 | .01 |
| | 400 | 15 | .01 | .01 | .01 | .01 | .01 | .00 | .02 | .02 | .02 | .01 | .01 | .00 | .02 | .02 | .02 | .01 | .01 | .00 | .03 | .03 | .03 | .01 | .01 | .00 |
| | | 30 | .02 | .02 | .02 | .01 | .01 | .00 | .03 | .03 | .03 | .01 | .01 | .00 | .04 | .04 | .04 | .02 | .01 | .00 | .05 | .05 | .04 | .02 | .01 | .00 |
| | | 100 | .04 | .04 | .04 | .01 | .01 | .00 | .06 | .06 | .05 | .01 | .02 | .00 | .07 | .07 | .07 | .03 | .03 | .00 | .08 | .08 | .08 | .03 | .02 | .00 |
| Heavy Skew | 30 | 15 | .04 | .04 | .04 | .03 | .04 | .04 | .06 | .06 | .06 | .03 | .06 | .04 | .05 | .05 | .05 | .04 | .04 | .03 | .06 | .06 | .06 | .04 | .04 | .03 |
| | | 30 | .05 | .05 | .05 | .03 | .04 | .04 | .07 | .08 | .08 | .03 | .06 | .04 | .05 | .05 | .05 | .04 | .04 | .04 | .07 | .07 | .07 | .04 | .04 | .04 |
| | | 100 | .06 | .07 | .06 | .04 | .04 | .03 | .11 | .11 | .10 | .04 | .08 | .03 | .08 | .08 | .08 | .05 | .04 | .04 | .10 | .10 | .10 | .05 | .04 | .04 |
| | 60 | 15 | .02 | .02 | .03 | .02 | .02 | .02 | .04 | .05 | .05 | .02 | .04 | .02 | .03 | .03 | .03 | .02 | .02 | .02 | .04 | .04 | .04 | .02 | .02 | .02 |
| | | 30 | .03 | .04 | .03 | .02 | .02 | .02 | .06 | .06 | .06 | .02 | .05 | .02 | .04 | .04 | .04 | .02 | .02 | .02 | .06 | .06 | .06 | .03 | .02 | .02 |
| | | 100 | .05 | .05 | .05 | .02 | .03 | .02 | .09 | .09 | .09 | .02 | .06 | .02 | .07 | .07 | .07 | .03 | .02 | .02 | .09 | .08 | .08 | .04 | .02 | .02 |
| | 120 | 15 | .01 | .02 | .02 | .01 | .01 | .01 | .03 | .04 | .04 | .01 | .03 | .01 | .02 | .02 | .02 | .01 | .01 | .01 | .03 | .03 | .03 | .01 | .01 | .01 |
| | | 30 | .02 | .03 | .03 | .01 | .02 | .01 | .05 | .06 | .06 | .01 | .04 | .01 | .04 | .03 | .03 | .02 | .01 | .01 | .05 | .05 | .05 | .02 | .01 | .01 |
| | | 100 | .04 | .04 | .04 | .01 | .02 | .01 | .08 | .08 | .08 | .01 | .05 | .01 | .07 | .06 | .06 | .02 | .02 | .01 | .08 | .08 | .08 | .03 | .01 | .01 |
| | 400 | 15 | .01 | .01 | .01 | .00 | .01 | .00 | .03 | .03 | .03 | .00 | .03 | .00 | .02 | .02 | .02 | .01 | .00 | .00 | .03 | .03 | .03 | .01 | .00 | .00 |
| | | 30 | .02 | .02 | .02 | .00 | .01 | .00 | .05 | .05 | .05 | .00 | .03 | .00 | .03 | .03 | .03 | .01 | .01 | .00 | .05 | .05 | .05 | .02 | .00 | .00 |
| | | 100 | .04 | .04 | .04 | .01 | .01 | .00 | .08 | .08 | .08 | .00 | .05 | .00 | .06 | .06 | .06 | .02 | .01 | .00 | .08 | .08 | .08 | .03 | .00 | .00 |

## $sr^2$, Effect Size = .50

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .04 | .04 | .04 | .03 | .03 | .03 | .04 | .04 | .04 | .03 | .03 | .03 | .06 | .05 | .05 | .04 | .05 | .04 | .06 | .05 | .05 | .04 | .04 | .04 |
| | | 30 | .07 | .07 | .07 | .04 | .04 | .03 | .07 | .07 | .07 | .04 | .03 | .03 | .13 | .12 | .12 | .08 | .10 | .06 | .13 | .12 | .12 | .08 | .09 | .06 |
| | | 100 | .12 | .11 | .11 | .04 | .05 | .04 | .12 | .11 | .11 | .04 | .04 | .04 | .19 | .19 | .19 | .10 | .15 | .07 | .19 | .19 | .19 | .10 | .14 | .07 |
| | 60 | 15 | .04 | .04 | .04 | .02 | .02 | .02 | .04 | .04 | .04 | .02 | .02 | .02 | .08 | .08 | .08 | .04 | .06 | .03 | .08 | .08 | .08 | .04 | .05 | .03 |
| | | 30 | .06 | .05 | .05 | .02 | .02 | .02 | .06 | .05 | .05 | .02 | .02 | .02 | .13 | .12 | .12 | .07 | .09 | .03 | .13 | .12 | .12 | .07 | .08 | .03 |
| | | 100 | .11 | .09 | .10 | .02 | .03 | .02 | .11 | .09 | .10 | .02 | .02 | .02 | .18 | .18 | .18 | .09 | .15 | .04 | .18 | .18 | .18 | .09 | .13 | .04 |
| | 120 | 15 | .03 | .03 | .03 | .02 | .01 | .01 | .03 | .03 | .03 | .02 | .01 | .01 | .08 | .07 | .07 | .04 | .05 | .02 | .08 | .07 | .07 | .04 | .04 | .02 |
| | | 30 | .06 | .05 | .05 | .02 | .01 | .01 | .06 | .05 | .05 | .02 | .01 | .01 | .12 | .11 | .11 | .06 | .08 | .02 | .12 | .11 | .11 | .06 | .07 | .02 |
| | | 100 | .10 | .09 | .09 | .01 | .02 | .01 | .10 | .09 | .09 | .01 | .01 | .01 | .18 | .17 | .17 | .08 | .14 | .02 | .18 | .17 | .17 | .08 | .12 | .02 |
| | 400 | 15 | .03 | .03 | .03 | .01 | .00 | .00 | .03 | .03 | .03 | .01 | .00 | .00 | .08 | .07 | .07 | .03 | .05 | .01 | .08 | .07 | .07 | .03 | .04 | .01 |
| | | 30 | .05 | .05 | .05 | .01 | .01 | .00 | .05 | .05 | .05 | .01 | .00 | .00 | .12 | .11 | .11 | .06 | .08 | .01 | .12 | .11 | .11 | .06 | .07 | .01 |
| | | 100 | .10 | .09 | .09 | .01 | .01 | .00 | .10 | .09 | .09 | .01 | .00 | .00 | .18 | .17 | .17 | .08 | .13 | .01 | .18 | .17 | .17 | .08 | .12 | .01 |
| Moderate Skew | 30 | 15 | .06 | .06 | .06 | .04 | .04 | .03 | .07 | .07 | .07 | .04 | .05 | .04 | .09 | .09 | .08 | .05 | .06 | .03 | .10 | .10 | .10 | .06 | .05 | .04 |
| | | 30 | .08 | .07 | .08 | .05 | .04 | .04 | .09 | .09 | .09 | .05 | .04 | .04 | .13 | .12 | .12 | .07 | .07 | .04 | .14 | .13 | .13 | .07 | .07 | .04 |
| | | 100 | .12 | .11 | .11 | .05 | .04 | .03 | .14 | .13 | .13 | .05 | .05 | .03 | .19 | .18 | .18 | .08 | .11 | .03 | .20 | .20 | .20 | .09 | .10 | .03 |
| | 60 | 15 | .04 | .04 | .04 | .02 | .02 | .02 | .05 | .06 | .06 | .03 | .03 | .02 | .07 | .07 | .07 | .04 | .04 | .02 | .09 | .08 | .08 | .04 | .03 | .02 |
| | | 30 | .06 | .06 | .06 | .03 | .02 | .02 | .07 | .07 | .08 | .03 | .03 | .02 | .11 | .11 | .11 | .06 | .05 | .02 | .13 | .12 | .12 | .06 | .05 | .02 |
| | | 100 | .10 | .10 | .09 | .03 | .02 | .02 | .12 | .12 | .11 | .04 | .03 | .02 | .18 | .18 | .18 | .07 | .10 | .02 | .20 | .19 | .19 | .08 | .08 | .02 |
| | 120 | 15 | .03 | .03 | .03 | .02 | .01 | .01 | .05 | .05 | .05 | .02 | .02 | .01 | .06 | .06 | .06 | .03 | .03 | .01 | .08 | .07 | .07 | .03 | .02 | .01 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 30 | .06 | .05 | .06 | .02 | .01 | .01 | .07 | .07 | .08 | .03 | .03 | .01 | .11 | .11 | .11 | .05 | .05 | .01 | .13 | .12 | .12 | .06 | .04 | .01 |
| | | 100 | .10 | .09 | .09 | .02 | .01 | .01 | .12 | .12 | .11 | .03 | .03 | .01 | .17 | .17 | .17 | .06 | .08 | .01 | .19 | .18 | .18 | .07 | .07 | .01 |
| | 400 | 15 | .03 | .03 | .03 | .01 | .01 | .00 | .04 | .04 | .05 | .01 | .02 | .01 | .07 | .06 | .06 | .03 | .02 | .00 | .08 | .08 | .07 | .03 | .02 | .00 |
| | | 30 | .05 | .05 | .05 | .02 | .01 | .00 | .07 | .07 | .07 | .02 | .02 | .01 | .11 | .10 | .10 | .05 | .04 | .00 | .12 | .11 | .11 | .05 | .03 | .00 |
| | | 100 | .10 | .09 | .09 | .02 | .01 | .00 | .12 | .11 | .11 | .03 | .02 | .00 | .18 | .17 | .17 | .06 | .08 | .00 | .19 | .19 | .19 | .07 | .06 | .00 |
| Heavy Skew | 30 | 15 | .05 | .05 | .06 | .04 | .04 | .04 | .07 | .08 | .08 | .04 | .06 | .04 | .07 | .07 | .07 | .05 | .04 | .04 | .09 | .09 | .09 | .05 | .04 | .04 |
| | | 30 | .07 | .08 | .07 | .04 | .04 | .04 | .11 | .11 | .11 | .04 | .08 | .04 | .10 | .10 | .10 | .05 | .05 | .04 | .12 | .12 | .12 | .06 | .05 | .04 |
| | | 100 | .11 | .11 | .09 | .05 | .05 | .04 | .16 | .16 | .15 | .04 | .10 | .04 | .17 | .17 | .17 | .07 | .08 | .04 | .20 | .20 | .19 | .09 | .06 | .04 |
| | 60 | 15 | .03 | .04 | .04 | .02 | .02 | .02 | .06 | .06 | .06 | .02 | .05 | .02 | .06 | .05 | .05 | .03 | .02 | .02 | .07 | .07 | .07 | .03 | .02 | .02 |
| | | 30 | .06 | .06 | .06 | .02 | .03 | .02 | .10 | .10 | .10 | .02 | .07 | .02 | .09 | .09 | .09 | .04 | .03 | .02 | .12 | .11 | .11 | .05 | .03 | .02 |
| | | 100 | .10 | .10 | .08 | .03 | .03 | .02 | .15 | .15 | .14 | .02 | .08 | .02 | .17 | .16 | .16 | .05 | .05 | .02 | .19 | .19 | .18 | .07 | .04 | .02 |
| | 120 | 15 | .03 | .03 | .03 | .01 | .02 | .01 | .05 | .06 | .06 | .01 | .04 | .01 | .05 | .05 | .05 | .02 | .02 | .01 | .07 | .07 | .07 | .02 | .01 | .01 |
| | | 30 | .05 | .06 | .05 | .01 | .02 | .01 | .09 | .09 | .09 | .01 | .06 | .01 | .09 | .09 | .09 | .03 | .02 | .01 | .11 | .11 | .11 | .04 | .02 | .01 |
| | | 100 | .10 | .09 | .08 | .02 | .03 | .01 | .15 | .14 | .14 | .01 | .08 | .01 | .16 | .16 | .16 | .05 | .04 | .01 | .19 | .18 | .18 | .07 | .02 | .01 |
| | 400 | 15 | .02 | .03 | .03 | .00 | .01 | .00 | .05 | .05 | .05 | .01 | .03 | .00 | .05 | .05 | .05 | .01 | .01 | .00 | .07 | .07 | .07 | .02 | .01 | .00 |
| | | 30 | .04 | .05 | .05 | .00 | .02 | .00 | .08 | .09 | .09 | .01 | .05 | .00 | .09 | .08 | .08 | .03 | .02 | .00 | .11 | .11 | .11 | .04 | .01 | .00 |
| | | 100 | .09 | .09 | .08 | .01 | .02 | .00 | .14 | .14 | .13 | .00 | .07 | .00 | .16 | .16 | .16 | .05 | .03 | .00 | .19 | .18 | .18 | .06 | .02 | .00 |

## APPENDIX E: $R^2$ for each condition

### $R^2$, Effect Size = .10

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 11 | 11 | 11 | 11 | 11 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 12 | 12 | 12 |
| | | 30 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 12 | 12 | 12 | 12 | 14 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| | | 100 | 14 | 14 | 14 | 13 | 14 | 14 | 13 | 13 | 13 | 12 | 13 | 13 | 15 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 |
| | 60 | 15 | 09 | 09 | 09 | 09 | 09 | 09 | 08 | 08 | 08 | 08 | 08 | 08 | 10 | 10 | 10 | 10 | 10 | 10 | 09 | 09 | 09 | 09 | 09 | 09 |
| | | 30 | 10 | 10 | 10 | 10 | 10 | 10 | 09 | 09 | 09 | 09 | 09 | 09 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 |
| | | 100 | 11 | 10 | 10 | 10 | 10 | 10 | 09 | 09 | 09 | 08 | 09 | 09 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 10 |
| | 120 | 15 | 07 | 07 | 07 | 07 | 07 | 07 | 06 | 06 | 06 | 06 | 06 | 06 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 07 |
| | | 30 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 07 | 07 | 07 | 07 | 07 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 08 |
| | | 100 | 09 | 09 | 09 | 09 | 09 | 09 | 08 | 08 | 08 | 08 | 08 | 08 | 10 | 10 | 10 | 10 | 10 | 09 | 10 | 10 | 10 | 09 | 09 | 09 |
| | 400 | 15 | 06 | 06 | 06 | 06 | 06 | 06 | 05 | 05 | 05 | 05 | 05 | 05 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 |
| | | 30 | 07 | 07 | 07 | 07 | 07 | 07 | 06 | 06 | 06 | 06 | 06 | 06 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 07 |
| | | 100 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 07 | 07 | 06 | 07 | 06 | 09 | 09 | 09 | 08 | 09 | 08 | 09 | 09 | 09 | 08 | 08 | 08 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moderate Skew | 30 | 15 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 13 | 12 | 14 | 14 | 14 | 14 | 14 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| | | 30 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 13 | 13 | 12 | 12 | 12 | 14 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| | | 100 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 11 | 14 | 14 | 14 | 14 | 13 | 13 | 14 | 14 | 14 | 13 | 13 | 13 |
| | 60 | 15 | 09 | 09 | 09 | 09 | 09 | 09 | 08 | 08 | 08 | 08 | 09 | 08 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 09 | 09 | 09 |
| | | 30 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 09 | 10 | 09 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 10 | 10 | 10 |
| | | 100 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 09 | 10 | 09 | 11 | 11 | 11 | 10 | 10 | 10 | 11 | 11 | 11 | 10 | 10 | 10 |
| | 120 | 15 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 07 | 07 | 06 | 07 | 06 | 09 | 09 | 09 | 09 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 |
| | | 30 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 08 | 07 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 08 | 08 | 08 |
| | | 100 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 07 | 08 | 07 | 10 | 10 | 10 | 09 | 09 | 09 | 10 | 10 | 10 | 09 | 09 | 09 |
| | 400 | 15 | 07 | 07 | 07 | 07 | 07 | 07 | 06 | 06 | 06 | 05 | 06 | 05 | 08 | 08 | 08 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 |
| | | 30 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 06 | 07 | 06 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 07 | 07 |
| | | 100 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 06 | 07 | 06 | 09 | 09 | 09 | 08 | 08 | 08 | 09 | 09 | 09 | 08 | 08 | 08 |
| Heavy Skew | 30 | 15 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 12 | 12 | 10 | 12 | 10 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 12 | 12 |
| | | 30 | 12 | 12 | 12 | 12 | 12 | 12 | 11 | 12 | 12 | 09 | 12 | 10 | 13 | 13 | 13 | 12 | 12 | 12 | 13 | 13 | 13 | 12 | 12 | 12 |
| | | 100 | 14 | 14 | 14 | 13 | 14 | 13 | 13 | 14 | 14 | 09 | 13 | 10 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 13 | 13 | 13 |
| | 60 | 15 | 08 | 08 | 08 | 08 | 08 | 08 | 07 | 07 | 07 | 06 | 07 | 06 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 08 | 08 | 08 |
| | | 30 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 09 | 07 | 09 | 07 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 09 | 09 | 09 |
| | | 100 | 10 | 10 | 11 | 10 | 10 | 10 | 10 | 10 | 10 | 07 | 10 | 07 | 11 | 11 | 11 | 10 | 10 | 10 | 11 | 11 | 11 | 10 | 09 | 09 |
| | 120 | 15 | 06 | 07 | 07 | 06 | 07 | 06 | 06 | 06 | 06 | 05 | 06 | 05 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 |
| | | 30 | 08 | 08 | 08 | 07 | 08 | 07 | 07 | 08 | 08 | 05 | 07 | 05 | 08 | 08 | 09 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 | 08 |
| | | 100 | 09 | 09 | 10 | 09 | 09 | 09 | 09 | 09 | 09 | 06 | 08 | 06 | 10 | 10 | 10 | 09 | 09 | 09 | 10 | 10 | 10 | 09 | 08 | 08 |
| | 400 | 15 | 05 | 05 | 05 | 05 | 06 | 05 | 05 | 05 | 05 | 04 | 05 | 04 | 06 | 06 | 06 | 06 | 06 | 06 | 06 | 06 | 06 | 06 | 06 | 06 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 30 | 07 | 07 | 07 | 06 | 07 | 06 | 06 | 07 | 07 | 04 | 06 | 04 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 07 | 06 | 06 |
| | | 100 | 08 | 08 | 08 | 07 | 08 | 07 | 08 | 08 | 08 | 04 | 07 | 04 | 09 | 09 | 09 | 08 | 08 | 08 | 08 | 09 | 09 | 07 | 07 | 07 |

## $R^2$, Effect Size = .30

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 12 | 12 | 12 | 11 | 15 | 15 | 15 | 14 | 15 | 14 | 15 | 15 | 15 | 14 | 14 | 13 |
| | | 30 | 15 | 15 | 15 | 13 | 14 | 13 | 14 | 14 | 14 | 12 | 12 | 12 | 17 | 17 | 17 | 15 | 16 | 15 | 17 | 17 | 17 | 15 | 15 | 14 |
| | | 100 | 16 | 16 | 16 | 13 | 14 | 13 | 15 | 14 | 14 | 11 | 12 | 12 | 19 | 19 | 19 | 16 | 18 | 15 | 19 | 19 | 19 | 16 | 17 | 15 |
| | 60 | 15 | 10 | 10 | 10 | 09 | 09 | 09 | 09 | 08 | 08 | 08 | 08 | 08 | 12 | 12 | 12 | 11 | 11 | 10 | 12 | 11 | 11 | 10 | 10 | 10 |
| | | 30 | 11 | 11 | 11 | 09 | 10 | 09 | 10 | 10 | 10 | 09 | 09 | 09 | 14 | 13 | 13 | 12 | 13 | 11 | 13 | 13 | 13 | 11 | 12 | 10 |
| | | 100 | 14 | 14 | 14 | 11 | 11 | 11 | 13 | 12 | 12 | 09 | 10 | 10 | 17 | 17 | 17 | 13 | 16 | 12 | 17 | 17 | 17 | 13 | 15 | 12 |
| | 120 | 15 | 08 | 08 | 08 | 08 | 07 | 07 | 07 | 07 | 07 | 06 | 06 | 06 | 11 | 10 | 10 | 09 | 10 | 08 | 10 | 10 | 10 | 09 | 09 | 08 |
| | | 30 | 10 | 10 | 10 | 09 | 09 | 09 | 09 | 09 | 09 | 08 | 07 | 07 | 13 | 13 | 13 | 11 | 12 | 10 | 13 | 12 | 12 | 11 | 11 | 09 |
| | | 100 | 12 | 12 | 12 | 09 | 09 | 09 | 11 | 10 | 10 | 07 | 08 | 07 | 15 | 15 | 15 | 12 | 14 | 10 | 15 | 15 | 15 | 12 | 13 | 09 |
| | 400 | 15 | 07 | 07 | 07 | 07 | 06 | 06 | 06 | 06 | 06 | 05 | 05 | 05 | 10 | 10 | 10 | 08 | 09 | 07 | 09 | 09 | 09 | 08 | 08 | 07 |
| | | 30 | 09 | 09 | 09 | 07 | 07 | 07 | 08 | 07 | 07 | 06 | 06 | 06 | 11 | 11 | 11 | 09 | 10 | 08 | 11 | 11 | 11 | 09 | 09 | 07 |
| | | 100 | 12 | 11 | 11 | 08 | 08 | 08 | 10 | 10 | 10 | 07 | 07 | 06 | 15 | 14 | 14 | 11 | 13 | 08 | 14 | 14 | 14 | 11 | 12 | 08 |
| Moderate Skew | 30 | 15 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 11 | 12 | 11 | 15 | 15 | 15 | 14 | 14 | 13 | 15 | 15 | 14 | 13 | 13 | 13 |
| | | 30 | 14 | 14 | 14 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 11 | 16 | 16 | 16 | 14 | 14 | 13 | 16 | 15 | 15 | 13 | 13 | 12 |
| | | 100 | 17 | 17 | 16 | 14 | 14 | 14 | 17 | 17 | 16 | 13 | 13 | 12 | 19 | 19 | 19 | 16 | 16 | 14 | 19 | 19 | 19 | 15 | 15 | 13 |
| | 60 | 15 | 10 | 10 | 10 | 09 | 09 | 09 | 10 | 10 | 10 | 08 | 08 | 08 | 12 | 12 | 12 | 11 | 11 | 10 | 12 | 12 | 12 | 10 | 09 | 09 |
| | | 30 | 11 | 11 | 11 | 10 | 10 | 10 | 11 | 11 | 11 | 09 | 09 | 08 | 14 | 13 | 13 | 11 | 11 | 10 | 14 | 13 | 13 | 11 | 10 | 09 |
| | | 100 | 14 | 14 | 14 | 11 | 11 | 11 | 14 | 14 | 13 | 10 | 10 | 09 | 17 | 17 | 17 | 13 | 13 | 11 | 17 | 17 | 17 | 12 | 12 | 10 |
| | 120 | 15 | 08 | 08 | 08 | 08 | 08 | 07 | 08 | 08 | 08 | 06 | 07 | 06 | 10 | 10 | 10 | 09 | 09 | 08 | 10 | 10 | 10 | 08 | 08 | 07 |
| | | 30 | 10 | 10 | 10 | 09 | 09 | 09 | 10 | 10 | 10 | 08 | 08 | 07 | 13 | 12 | 12 | 11 | 10 | 09 | 13 | 12 | 12 | 10 | 09 | 08 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 100 | 12 | 12 | 12 | 09 | 09 | 09 | 12 | 12 | 12 | 08 | 08 | 07 | 15 | 15 | 15 | 11 | 12 | 09 | 15 | 15 | 15 | 11 | 10 | 08 |
| | 400 | 15 | 07 | 07 | 07 | 07 | 07 | 06 | 07 | 07 | 07 | 05 | 06 | 05 | 09 | 09 | 09 | 08 | 08 | 07 | 09 | 09 | 09 | 07 | 07 | 06 |
| | | 30 | 09 | 09 | 09 | 08 | 07 | 07 | 08 | 09 | 08 | 06 | 07 | 06 | 11 | 11 | 11 | 09 | 09 | 08 | 11 | 11 | 11 | 08 | 08 | 07 |
| | | 100 | 12 | 11 | 11 | 09 | 08 | 08 | 11 | 11 | 11 | 07 | 08 | 06 | 15 | 15 | 15 | 11 | 11 | 08 | 15 | 15 | 15 | 10 | 09 | 07 |
| Heavy Skew | 30 | 15 | 11 | 12 | 12 | 11 | 12 | 11 | 11 | 12 | 12 | 08 | 11 | 09 | 13 | 13 | 13 | 12 | 13 | 12 | 13 | 13 | 13 | 11 | 11 | 11 |
| | | 30 | 13 | 13 | 13 | 12 | 12 | 12 | 13 | 13 | 13 | 08 | 12 | 10 | 15 | 15 | 15 | 13 | 13 | 13 | 15 | 15 | 15 | 12 | 11 | 12 |
| | | 100 | 16 | 16 | 16 | 14 | 14 | 13 | 16 | 16 | 16 | 08 | 13 | 09 | 19 | 18 | 18 | 15 | 15 | 14 | 19 | 18 | 18 | 14 | 13 | 12 |
| | 60 | 15 | 08 | 09 | 09 | 08 | 09 | 08 | 08 | 08 | 09 | 06 | 08 | 06 | 10 | 10 | 10 | 09 | 09 | 09 | 10 | 10 | 10 | 08 | 08 | 08 |
| | | 30 | 10 | 10 | 10 | 09 | 09 | 09 | 10 | 10 | 10 | 06 | 09 | 06 | 12 | 12 | 12 | 10 | 10 | 10 | 12 | 12 | 12 | 09 | 08 | 08 |
| | | 100 | 14 | 14 | 13 | 11 | 11 | 10 | 14 | 14 | 13 | 06 | 11 | 06 | 16 | 16 | 16 | 12 | 11 | 11 | 16 | 16 | 16 | 11 | 09 | 09 |
| | 120 | 15 | 07 | 07 | 07 | 06 | 07 | 06 | 06 | 07 | 07 | 04 | 06 | 04 | 09 | 08 | 09 | 08 | 07 | 07 | 08 | 08 | 08 | 06 | 06 | 06 |
| | | 30 | 09 | 09 | 09 | 08 | 08 | 08 | 09 | 09 | 09 | 05 | 08 | 04 | 11 | 11 | 11 | 09 | 09 | 08 | 11 | 11 | 11 | 08 | 07 | 07 |
| | | 100 | 12 | 12 | 12 | 09 | 10 | 08 | 12 | 12 | 12 | 04 | 09 | 04 | 15 | 15 | 15 | 11 | 10 | 09 | 15 | 15 | 15 | 10 | 08 | 07 |
| | 400 | 15 | 06 | 06 | 06 | 05 | 06 | 05 | 05 | 06 | 06 | 03 | 05 | 03 | 07 | 07 | 07 | 06 | 06 | 06 | 07 | 07 | 07 | 05 | 05 | 05 |
| | | 30 | 07 | 08 | 08 | 06 | 07 | 06 | 07 | 08 | 08 | 03 | 06 | 03 | 10 | 10 | 10 | 08 | 07 | 07 | 10 | 10 | 10 | 07 | 05 | 05 |
| | | 100 | 11 | 11 | 11 | 08 | 08 | 07 | 11 | 11 | 11 | 03 | 08 | 03 | 14 | 14 | 14 | 10 | 08 | 08 | 14 | 14 | 14 | 09 | 06 | 06 |

## $R^2$, Effect Size = .50

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | 13 | 13 | 13 | 13 | 13 | 13 | 12 | 12 | 12 | 12 | 12 | 11 | 15 | 15 | 15 | 14 | 15 | 14 | 15 | 15 | 15 | 14 | 14 | 13 |
| | | 30 | 17 | 16 | 16 | 14 | 14 | 13 | 16 | 15 | 15 | 13 | 12 | 12 | 23 | 22 | 22 | 18 | 20 | 16 | 23 | 22 | 22 | 17 | 19 | 15 |
| | | 100 | 22 | 21 | 21 | 12 | 14 | 13 | 20 | 19 | 19 | 11 | 12 | 12 | 29 | 28 | 28 | 20 | 25 | 17 | 29 | 28 | 28 | 20 | 23 | 16 |
| | 60 | 15 | 11 | 11 | 11 | 09 | 09 | 09 | 10 | 10 | 10 | 08 | 08 | 08 | 16 | 15 | 15 | 12 | 14 | 11 | 16 | 15 | 15 | 12 | 12 | 10 |
| | | 30 | 14 | 14 | 14 | 11 | 10 | 10 | 13 | 13 | 13 | 09 | 09 | 09 | 21 | 21 | 21 | 15 | 18 | 12 | 21 | 20 | 20 | 15 | 17 | 12 |
| | | 100 | 19 | 18 | 18 | 11 | 12 | 10 | 18 | 17 | 17 | 09 | 09 | 09 | 28 | 27 | 27 | 18 | 24 | 13 | 27 | 27 | 27 | 18 | 22 | 13 |
| | 120 | 15 | 10 | 10 | 10 | 08 | 08 | 08 | 09 | 08 | 09 | 07 | 06 | 06 | 15 | 14 | 14 | 11 | 13 | 09 | 15 | 14 | 14 | 10 | 11 | 08 |
| | | 30 | 13 | 13 | 13 | 09 | 09 | 08 | 12 | 12 | 12 | 08 | 07 | 07 | 20 | 19 | 19 | 14 | 16 | 10 | 20 | 19 | 19 | 14 | 15 | 09 |
| | | 100 | 18 | 17 | 17 | 10 | 10 | 09 | 17 | 16 | 16 | 08 | 08 | 08 | 26 | 26 | 26 | 17 | 22 | 11 | 26 | 26 | 26 | 16 | 21 | 10 |
| | 400 | 15 | 09 | 09 | 09 | 07 | 06 | 06 | 08 | 08 | 08 | 06 | 05 | 05 | 14 | 14 | 14 | 10 | 12 | 07 | 14 | 13 | 13 | 09 | 10 | 07 |
| | | 30 | 12 | 11 | 11 | 08 | 07 | 07 | 11 | 10 | 10 | 07 | 06 | 06 | 19 | 18 | 18 | 13 | 15 | 08 | 19 | 18 | 18 | 13 | 14 | 08 |
| | | 100 | 18 | 17 | 17 | 08 | 09 | 08 | 16 | 15 | 15 | 07 | 07 | 06 | 26 | 25 | 25 | 16 | 21 | 08 | 26 | 25 | 25 | 16 | 20 | 08 |
| Moderate Skew | 30 | 15 | 15 | 15 | 15 | 13 | 13 | 13 | 14 | 14 | 15 | 12 | 12 | 11 | 19 | 18 | 18 | 15 | 15 | 13 | 19 | 18 | 18 | 14 | 14 | 12 |
| | | 30 | 17 | 17 | 17 | 14 | 13 | 13 | 17 | 17 | 17 | 13 | 12 | 12 | 22 | 22 | 22 | 17 | 17 | 13 | 22 | 22 | 22 | 16 | 15 | 12 |
| | | 100 | 22 | 22 | 21 | 15 | 15 | 14 | 22 | 21 | 21 | 14 | 14 | 12 | 30 | 29 | 29 | 19 | 22 | 14 | 30 | 29 | 29 | 18 | 19 | 13 |
| | 60 | 15 | 11 | 11 | 12 | 10 | 10 | 09 | 11 | 11 | 11 | 08 | 09 | 08 | 16 | 15 | 15 | 12 | 12 | 10 | 16 | 15 | 15 | 11 | 10 | 09 |
| | | 30 | 14 | 14 | 14 | 11 | 10 | 10 | 14 | 14 | 14 | 10 | 10 | 09 | 20 | 20 | 19 | 14 | 14 | 11 | 20 | 20 | 19 | 13 | 12 | 09 |
| | | 100 | 19 | 18 | 18 | 12 | 11 | 10 | 19 | 19 | 18 | 11 | 10 | 09 | 27 | 27 | 27 | 16 | 19 | 11 | 27 | 27 | 27 | 15 | 15 | 09 |
| | 120 | 15 | 10 | 10 | 10 | 08 | 08 | 08 | 10 | 10 | 10 | 07 | 07 | 06 | 14 | 13 | 13 | 10 | 10 | 08 | 14 | 13 | 13 | 09 | 08 | 07 |
| | | 30 | 13 | 13 | 13 | 10 | 09 | 08 | 13 | 13 | 13 | 08 | 08 | 07 | 19 | 19 | 19 | 13 | 13 | 09 | 19 | 19 | 19 | 12 | 11 | 08 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 100 | 18 | 18 | 17 | 11 | 10 | 09 | 18 | 18 | 17 | 09 | 09 | 07 | 26 | 25 | 25 | 15 | 17 | 09 | 26 | 25 | 25 | 14 | 14 | 08 |
| | 400 | 15 | 09 | 09 | 09 | 07 | 07 | 07 | 09 | 09 | 09 | 06 | 06 | 05 | 14 | 13 | 13 | 09 | 09 | 07 | 13 | 13 | 13 | 08 | 07 | 06 |
| | | 30 | 12 | 12 | 12 | 09 | 08 | 07 | 12 | 12 | 12 | 07 | 07 | 06 | 18 | 17 | 17 | 12 | 11 | 08 | 18 | 17 | 17 | 11 | 09 | 06 |
| | | 100 | 17 | 17 | 16 | 10 | 08 | 08 | 17 | 17 | 16 | 08 | 08 | 06 | 25 | 25 | 25 | 14 | 15 | 08 | 25 | 25 | 25 | 13 | 12 | 06 |
| Heavy Skew | 30 | 15 | 13 | 13 | 13 | 11 | 12 | 11 | 12 | 13 | 13 | 08 | 11 | 09 | 16 | 16 | 16 | 13 | 13 | 13 | 16 | 16 | 16 | 12 | 11 | 11 |
| | | 30 | 15 | 16 | 16 | 13 | 13 | 12 | 15 | 16 | 16 | 08 | 12 | 08 | 20 | 19 | 19 | 14 | 14 | 13 | 20 | 19 | 19 | 13 | 12 | 11 |
| | | 100 | 21 | 21 | 20 | 15 | 15 | 14 | 21 | 21 | 20 | 06 | 15 | 08 | 28 | 28 | 27 | 17 | 18 | 14 | 28 | 28 | 27 | 17 | 14 | 12 |
| | 60 | 15 | 09 | 10 | 10 | 08 | 08 | 08 | 09 | 10 | 10 | 05 | 08 | 05 | 13 | 12 | 12 | 10 | 10 | 09 | 13 | 12 | 12 | 08 | 08 | 07 |
| | | 30 | 13 | 14 | 13 | 09 | 10 | 09 | 13 | 14 | 13 | 05 | 10 | 05 | 17 | 17 | 17 | 12 | 11 | 10 | 17 | 17 | 17 | 11 | 08 | 08 |
| | | 100 | 18 | 18 | 17 | 11 | 12 | 10 | 18 | 18 | 17 | 05 | 12 | 05 | 25 | 25 | 25 | 14 | 14 | 11 | 25 | 25 | 25 | 13 | 10 | 08 |
| | 120 | 15 | 08 | 08 | 08 | 06 | 07 | 06 | 07 | 08 | 08 | 04 | 06 | 03 | 11 | 11 | 11 | 08 | 08 | 07 | 11 | 11 | 11 | 07 | 05 | 05 |
| | | 30 | 11 | 12 | 12 | 07 | 09 | 07 | 11 | 12 | 12 | 04 | 08 | 03 | 16 | 16 | 16 | 10 | 09 | 08 | 16 | 16 | 16 | 09 | 07 | 06 |
| | | 100 | 17 | 17 | 16 | 10 | 10 | 09 | 17 | 17 | 16 | 03 | 10 | 03 | 24 | 24 | 24 | 13 | 12 | 09 | 24 | 24 | 24 | 13 | 08 | 07 |
| | 400 | 15 | 07 | 07 | 07 | 05 | 06 | 05 | 07 | 07 | 07 | 02 | 05 | 02 | 10 | 10 | 10 | 07 | 06 | 06 | 10 | 10 | 10 | 06 | 04 | 04 |
| | | 30 | 10 | 11 | 11 | 06 | 08 | 06 | 10 | 11 | 11 | 03 | 07 | 02 | 15 | 15 | 15 | 09 | 08 | 07 | 15 | 15 | 15 | 08 | 05 | 05 |
| | | 100 | 16 | 16 | 15 | 08 | 09 | 07 | 16 | 16 | 15 | 02 | 09 | 02 | 23 | 23 | 23 | 12 | 11 | 08 | 23 | 23 | 23 | 11 | 06 | 05 |

## APPENDIX F: VIF for each condition

### VIF, Effect Size = .10

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .06 | .05 | .06 | .08 | .10 | .35 | .06 | .05 | .05 | .08 | .58 | .25 | .05 | .05 | .05 | .04 | .27 | .46 | .05 | .05 | .05 | .04 | .10 | .41 |
| | | 30 | .08 | .07 | .07 | .10 | .88 | .48 | .07 | .06 | .06 | .11 | .38 | .36 | .05 | .05 | .05 | .04 | .96 | .60 | .05 | .05 | .05 | .04 | .78 | .57 |
| | | 100 | .10 | .09 | .10 | .19 | 0.47 | .74 | .10 | .08 | .09 | .23 | .99 | .49 | .06 | .06 | .06 | .04 | .23 | .91 | .06 | .06 | .06 | .04 | .95 | .86 |
| | 60 | 15 | .03 | .02 | .03 | .03 | .75 | .17 | .03 | .02 | .02 | .03 | .47 | .13 | .02 | .02 | .02 | .02 | .18 | .30 | .02 | .02 | .02 | .02 | .02 | .27 |
| | | 30 | .04 | .03 | .03 | .05 | .38 | .19 | .03 | .03 | .03 | .05 | .19 | .15 | .03 | .03 | .03 | .02 | .81 | .39 | .03 | .02 | .02 | .02 | .63 | .36 |
| | | 100 | .05 | .04 | .05 | .09 | .18 | .24 | .04 | .04 | .04 | .11 | .65 | .17 | .03 | .03 | .03 | .02 | .97 | .53 | .03 | .03 | .03 | .02 | .72 | .50 |
| | 120 | 15 | .01 | .01 | .01 | .02 | .65 | .09 | .01 | .01 | .01 | .02 | .40 | .07 | .01 | .01 | .01 | .01 | .16 | .16 | .01 | .01 | .01 | .01 | .00 | .15 |
| | | 30 | .02 | .01 | .02 | .02 | .17 | .08 | .02 | .01 | .02 | .03 | .12 | .07 | .01 | .01 | .01 | .01 | .80 | .21 | .01 | .01 | .01 | .01 | .62 | .20 |
| | | 100 | .02 | .02 | .02 | .05 | .53 | .09 | .02 | .02 | .02 | .06 | .57 | .07 | .01 | .01 | .01 | .01 | .96 | .26 | .01 | .01 | .01 | .01 | .72 | .25 |
| | 400 | 15 | .00 | .00 | .00 | .00 | .48 | .04 | .00 | .00 | .00 | .01 | .36 | .04 | .00 | .00 | .00 | .00 | .13 | .06 | .00 | .00 | .00 | .00 | .98 | .05 |
| | | 30 | .01 | .00 | .00 | .01 | .80 | .03 | .00 | .00 | .00 | .01 | .00 | .03 | .00 | .00 | .00 | .00 | .75 | .06 | .00 | .00 | .00 | .00 | .58 | .05 |
| | | 100 | .01 | .01 | .01 | .02 | .57 | .02 | .01 | .01 | .01 | .02 | .42 | .02 | .00 | .00 | .00 | .00 | .88 | .07 | .00 | .00 | .00 | .00 | .64 | .07 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Moderate Skew | 30 | 15 | .60 | .55 | .69 | .51 | .45 | .10 | .24 | .21 | .32 | .82 | .93 | .07 | .24 | .24 | .26 | .15 | .28 | .04 | .14 | .14 | .16 | .14 | .56 | .04 |
| | | 30 | .78 | .73 | .86 | .63 | .38 | .06 | .37 | .30 | .46 | .11 | .52 | .04 | .30 | .31 | .33 | .21 | .97 | .04 | .19 | .20 | .23 | .19 | .37 | .04 |
| | | 100 | .14 | .09 | .13 | .76 | .19 | .04 | .62 | .48 | .67 | .59 | .46 | .01 | .36 | .39 | .43 | .26 | .26 | .03 | .26 | .28 | .31 | .23 | .72 | .03 |
| | 60 | 15 | .54 | .48 | .60 | .45 | .16 | .09 | .21 | .18 | .28 | .70 | .67 | .06 | .20 | .20 | .22 | .12 | .17 | .02 | .11 | .11 | .13 | .11 | .41 | .02 |
| | | 30 | .69 | .63 | .74 | .55 | .88 | .05 | .32 | .27 | .41 | .95 | .12 | .03 | .26 | .26 | .29 | .17 | .83 | .01 | .16 | .16 | .19 | .15 | .20 | .01 |
| | | 100 | .99 | .93 | .99 | .69 | .18 | .02 | .55 | .42 | .60 | .42 | .12 | .01 | .31 | .33 | .37 | .22 | .06 | .01 | .22 | .23 | .27 | .20 | .49 | .01 |
| | 120 | 15 | .49 | .44 | .56 | .42 | .95 | .08 | .19 | .16 | .26 | .67 | .49 | .05 | .19 | .18 | .20 | .10 | .11 | .01 | .10 | .10 | .12 | .09 | .33 | .01 |
| | | 30 | .63 | .58 | .69 | .52 | .47 | .04 | .30 | .25 | .39 | .90 | .80 | .02 | .22 | .23 | .25 | .15 | .77 | .01 | .14 | .14 | .17 | .13 | .12 | .01 |
| | | 100 | .91 | .85 | .91 | .66 | .49 | .01 | .53 | .40 | .58 | .34 | .86 | .00 | .28 | .30 | .33 | .20 | .99 | .01 | .19 | .21 | .24 | .18 | .39 | .01 |
| | 400 | 15 | .47 | .42 | .53 | .39 | .78 | .07 | .18 | .15 | .25 | .62 | .33 | .05 | .17 | .17 | .19 | .09 | .09 | .00 | .09 | .09 | .11 | .08 | .31 | .00 |
| | | 30 | .60 | .55 | .65 | .49 | .13 | .04 | .29 | .24 | .37 | .84 | .54 | .02 | .21 | .21 | .23 | .14 | .73 | .00 | .12 | .13 | .15 | .12 | .08 | .00 |
| | | 100 | .86 | .80 | .86 | .63 | .89 | .01 | .50 | .39 | .55 | .28 | .62 | .00 | .26 | .28 | .31 | .20 | .90 | .00 | .18 | .20 | .23 | .17 | .29 | .00 |
| Heavy Skew | 30 | 15 | .49 | .82 | .49 | .10 | .81 | .10 | .25 | .25 | .51 | .69 | .79 | .12 | .59 | .69 | .81 | .39 | .96 | .06 | .23 | .27 | .36 | .38 | .50 | .06 |
| | | 30 | .85 | .15 | .08 | .51 | .22 | .07 | .36 | .33 | .66 | .20 | .82 | .10 | .71 | .90 | .08 | .57 | .57 | .06 | .34 | .43 | .57 | .52 | .29 | .06 |
| | | 100 | .51 | .39 | .41 | .63 | .13 | .07 | .49 | .38 | .72 | .30 | .78 | .09 | .89 | .22 | .49 | .81 | .78 | .06 | .51 | .69 | .87 | .75 | .45 | .06 |
| | 60 | 15 | .31 | .56 | .66 | .98 | .61 | .06 | .23 | .23 | .47 | .60 | .70 | .07 | .51 | .60 | .71 | .33 | .92 | .02 | .20 | .24 | .33 | .33 | .39 | .02 |
| | | 30 | .61 | .84 | .19 | .36 | .79 | .03 | .32 | .29 | .60 | .98 | .66 | .04 | .62 | .78 | .93 | .48 | .41 | .02 | .29 | .38 | .50 | .45 | .03 | .02 |
| | | 100 | .24 | .14 | .51 | .53 | .38 | .03 | .45 | .35 | .67 | 1.56 | .62 | .03 | .81 | .10 | .32 | .73 | .54 | .03 | .47 | .63 | .79 | .67 | .10 | .03 |
| | 120 | 15 | .21 | .43 | .37 | .92 | .54 | .04 | .21 | .21 | .44 | .11 | .66 | .05 | .48 | .56 | .67 | .32 | .86 | .01 | .18 | .22 | .30 | .31 | .32 | .01 |
| | | 30 | .49 | .67 | .75 | .29 | .61 | .02 | .31 | .28 | .58 | .56 | .59 | .03 | .58 | .73 | .87 | .45 | .38 | .01 | .27 | .35 | .47 | .42 | .98 | .01 |
| | | 100 | .05 | .96 | .08 | .45 | .94 | .01 | .42 | .33 | .64 | 3.59 | .52 | .02 | .74 | .01 | .23 | .68 | .45 | .01 | .43 | .59 | .75 | .63 | .97 | .01 |
| | 400 | 15 | .15 | .34 | .17 | .89 | .49 | .04 | .20 | .21 | .43 | .68 | .63 | .04 | .46 | .53 | .63 | .30 | .83 | .00 | .17 | .20 | .28 | .29 | .28 | .00 |
| | | 30 | .42 | .59 | .55 | .26 | .48 | .01 | .30 | .28 | .57 | .38 | .55 | .02 | .54 | .69 | .83 | .44 | .35 | .00 | .26 | .34 | .45 | .40 | .92 | .00 |
| | | 100 | .94 | .85 | .85 | .42 | .60 | .01 | .41 | .32 | .62 | 1.85 | .46 | .01 | .71 | .97 | .17 | .66 | .36 | .00 | .41 | .57 | .72 | .61 | .84 | .00 |

## VIF, Effect Size = .30

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .06 | .05 | .06 | .08 | .03 | .36 | .06 | .05 | .05 | .08 | .58 | .25 | .05 | .04 | .04 | .04 | .26 | .44 | .05 | .04 | .04 | .04 | .09 | .40 |
| | | 30 | .07 | .06 | .06 | .10 | .89 | .49 | .06 | .06 | .06 | .11 | .43 | .36 | .05 | .05 | .05 | .04 | .98 | .62 | .05 | .05 | .05 | .04 | .78 | .58 |
| | | 100 | .10 | .09 | .09 | .18 | 0.81 | .77 | .09 | .08 | .08 | .22 | .91 | .50 | .06 | .06 | .06 | .04 | .25 | .98 | .06 | .05 | .05 | .04 | .98 | .93 |
| | 60 | 15 | .03 | .02 | .03 | .03 | .80 | .15 | .03 | .02 | .02 | .04 | .47 | .12 | .02 | .02 | .02 | .02 | .21 | .27 | .02 | .02 | .02 | .02 | .04 | .24 |
| | | 30 | .03 | .03 | .03 | .05 | .38 | .21 | .03 | .03 | .03 | .05 | .19 | .16 | .02 | .02 | .02 | .02 | .87 | .38 | .02 | .02 | .02 | .02 | .68 | .36 |
| | | 100 | .05 | .04 | .05 | .09 | .40 | .24 | .04 | .04 | .04 | .12 | .67 | .17 | .03 | .03 | .03 | .02 | .07 | .51 | .03 | .03 | .03 | .02 | .79 | .49 |
| | 120 | 15 | .01 | .01 | .01 | .02 | .63 | .08 | .01 | .01 | .01 | .02 | .42 | .07 | .01 | .01 | .01 | .01 | .15 | .17 | .01 | .01 | .01 | .01 | .98 | .16 |
| | | 30 | .02 | .01 | .02 | .02 | .17 | .08 | .02 | .01 | .01 | .03 | .12 | .07 | .01 | .01 | .01 | .01 | .79 | .21 | .01 | .01 | .01 | .01 | .62 | .20 |
| | | 100 | .03 | .02 | .02 | .05 | .49 | .10 | .02 | .02 | .02 | .06 | .57 | .08 | .01 | .01 | .01 | .01 | .96 | .28 | .01 | .01 | .01 | .01 | .72 | .27 |
| | 400 | 15 | .00 | .00 | .00 | .01 | .46 | .04 | .00 | .00 | .00 | .01 | .34 | .04 | .00 | .00 | .00 | .00 | .13 | .06 | .00 | .00 | .00 | .00 | .98 | .05 |
| | | 30 | .01 | .00 | .00 | .01 | .82 | .03 | .00 | .00 | .00 | .01 | .00 | .03 | .00 | .00 | .00 | .00 | .76 | .06 | .00 | .00 | .00 | .00 | .59 | .06 |
| | | 100 | .01 | .01 | .01 | .01 | .62 | .02 | .01 | .01 | .01 | .02 | .45 | .02 | .00 | .00 | .00 | .00 | .91 | .07 | .00 | .00 | .00 | .00 | .66 | .07 |
| Moderate Skew | 30 | 15 | .59 | .54 | .67 | .50 | .42 | .10 | .23 | .20 | .31 | .82 | .94 | .07 | .25 | .25 | .26 | .14 | .26 | .04 | .14 | .14 | .17 | .14 | .51 | .04 |
| | | 30 | .75 | .70 | .81 | .60 | .46 | .06 | .36 | .30 | .44 | .04 | .60 | .04 | .28 | .29 | .32 | .19 | .97 | .03 | .18 | .19 | .22 | .18 | .38 | .03 |
| | | 100 | .10 | .05 | .10 | .76 | .33 | .03 | .60 | .47 | .66 | .55 | .53 | .01 | .35 | .38 | .42 | .26 | .37 | .03 | .25 | .27 | .31 | .23 | .85 | .03 |
| | 60 | 15 | .52 | .47 | .59 | .44 | .14 | .08 | .20 | .17 | .27 | .71 | .68 | .06 | .20 | .20 | .22 | .11 | .17 | .02 | .11 | .11 | .13 | .11 | .41 | .02 |
| | | 30 | .68 | .63 | .74 | .55 | .87 | .05 | .33 | .27 | .41 | .95 | .10 | .03 | .24 | .25 | .27 | .17 | .80 | .02 | .15 | .16 | .18 | .15 | .19 | .01 |
| | | 100 | .97 | .92 | .97 | .68 | .11 | .02 | .55 | .42 | .60 | .40 | .12 | .01 | .30 | .33 | .36 | .22 | .11 | .01 | .21 | .23 | .26 | .20 | .55 | .01 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 120 | 15 | .50 | .45 | .57 | .42 | .95 | .08 | .19 | .16 | .26 | .66 | .47 | .05 | .18 | .18 | .20 | .10 | .12 | .01 | .10 | .10 | .12 | .09 | .35 | .01 |
| | | 30 | .62 | .57 | .68 | .52 | .51 | .04 | .30 | .25 | .38 | .89 | .82 | .02 | .22 | .23 | .25 | .15 | .78 | .01 | .14 | .14 | .17 | .13 | .13 | .01 |
| | | 100 | .90 | .85 | .91 | .65 | .53 | .01 | .52 | .40 | .57 | .32 | .90 | .00 | .27 | .30 | .33 | .20 | .02 | .01 | .19 | .21 | .24 | .18 | .42 | .01 |
| | 400 | 15 | .47 | .42 | .53 | .39 | .79 | .07 | .18 | .15 | .25 | .61 | .34 | .05 | .17 | .17 | .19 | .09 | .10 | .00 | .09 | .09 | .11 | .09 | .32 | .00 |
| | | 30 | .59 | .54 | .64 | .50 | .16 | .04 | .29 | .24 | .37 | .85 | .57 | .02 | .21 | .21 | .23 | .14 | .74 | .00 | .12 | .13 | .15 | .12 | .09 | .00 |
| | | 100 | .85 | .80 | .86 | .64 | .87 | .01 | .50 | .39 | .55 | .29 | .61 | .00 | .26 | .28 | .31 | .19 | .94 | .00 | .18 | .19 | .23 | .17 | .33 | .00 |
| Heavy Skew | 30 | 15 | .43 | .75 | .31 | .08 | .80 | .08 | .25 | .25 | .51 | .56 | .80 | .10 | .59 | .68 | .80 | .40 | .97 | .06 | .22 | .27 | .36 | .39 | .54 | .06 |
| | | 30 | .78 | .05 | .77 | .51 | .20 | .07 | .36 | .33 | .66 | .91 | .82 | .09 | .68 | .87 | .05 | .55 | .56 | .06 | .33 | .43 | .56 | .51 | .23 | .06 |
| | | 100 | .52 | .41 | .02 | .65 | .13 | .06 | .48 | .38 | .72 | .60 | .78 | .09 | .88 | .21 | .48 | .79 | .80 | .06 | .51 | .70 | .88 | .74 | .43 | .06 |
| | 60 | 15 | .30 | .53 | .61 | .97 | .61 | .05 | .23 | .23 | .46 | .66 | .69 | .06 | .53 | .62 | .73 | .34 | .89 | .03 | .20 | .24 | .33 | .34 | .39 | .03 |
| | | 30 | .60 | .82 | .12 | .38 | .85 | .03 | .33 | .30 | .62 | .22 | .68 | .04 | .62 | .78 | .93 | .50 | .45 | .02 | .30 | .38 | .50 | .46 | .10 | .02 |
| | | 100 | .21 | .10 | .41 | .52 | .41 | .03 | .45 | .35 | .67 | 1.37 | .63 | .04 | .79 | .08 | .31 | .73 | .55 | .02 | .46 | .63 | .79 | .67 | .12 | .03 |
| | 120 | 15 | .21 | .43 | .38 | .93 | .55 | .04 | .21 | .21 | .45 | .22 | .67 | .05 | .49 | .57 | .67 | .32 | .86 | .01 | .18 | .22 | .30 | .31 | .32 | .01 |
| | | 30 | .50 | .68 | .78 | .31 | .59 | .02 | .31 | .29 | .59 | .72 | .59 | .02 | .58 | .74 | .88 | .46 | .39 | .01 | .28 | .36 | .48 | .43 | .98 | .01 |
| | | 100 | .04 | .94 | .05 | .46 | .00 | .01 | .43 | .34 | .64 | 3.76 | .55 | .02 | .73 | .01 | .22 | .68 | .44 | .01 | .43 | .59 | .75 | .63 | .95 | .01 |
| | 400 | 15 | .15 | .34 | .17 | .89 | .48 | .04 | .20 | .21 | .43 | .71 | .64 | .05 | .46 | .53 | .63 | .30 | .83 | .00 | .17 | .21 | .28 | .29 | .28 | .00 |
| | | 30 | .40 | .56 | .52 | .24 | .48 | .01 | .29 | .27 | .56 | .34 | .55 | .02 | .55 | .70 | .84 | .44 | .35 | .00 | .26 | .34 | .45 | .41 | .93 | .00 |
| | | 100 | .94 | .85 | .83 | .42 | .62 | .01 | .42 | .33 | .63 | 1.65 | .47 | .01 | .71 | .96 | .16 | .66 | .38 | .00 | .41 | .57 | .72 | .61 | .86 | .00 |

## VIF, Effect Size = .50

| | | | 1 Item | | | | | | | | | | | | 5 Items | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Controlling for Mean | | | | | | Controlling for Median | | | | | | Controlling for Mean | | | | | | Controlling for Median | | | | | |
| Distribution Shape | Obs | Nested Data Points | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg | SD | Adm | Admd | MAD | CV | awg |
| Normal | 30 | 15 | .06 | .05 | .06 | .08 | .03 | .36 | .06 | .05 | .05 | .08 | .58 | .25 | .05 | .04 | .04 | .04 | .26 | .44 | .05 | .04 | .04 | .04 | .09 | .40 |
| | | 30 | .07 | .06 | .06 | .09 | .98 | .47 | .06 | .05 | .05 | .10 | .37 | .34 | .05 | .04 | .05 | .04 | .95 | .64 | .05 | .04 | .04 | .04 | .74 | .58 |
| | | 100 | .11 | .10 | .10 | .19 | 0.48 | .72 | .10 | .08 | .09 | .24 | .92 | .46 | .07 | .07 | .07 | .04 | .32 | .92 | .07 | .06 | .06 | .04 | .03 | .86 |
| | 60 | 15 | .03 | .02 | .02 | .04 | .81 | .16 | .03 | .02 | .02 | .04 | .49 | .13 | .02 | .02 | .02 | .02 | .19 | .27 | .02 | .02 | .02 | .02 | .04 | .25 |
| | | 30 | .03 | .03 | .03 | .05 | .51 | .19 | .03 | .03 | .03 | .05 | .24 | .15 | .02 | .02 | .02 | .02 | .84 | .36 | .02 | .02 | .02 | .02 | .67 | .34 |
| | | 100 | .05 | .04 | .04 | .10 | .39 | .27 | .04 | .04 | .04 | .13 | .68 | .19 | .03 | .03 | .03 | .02 | .03 | .58 | .03 | .03 | .03 | .02 | .76 | .55 |
| | 120 | 15 | .01 | .01 | .01 | .02 | .66 | .08 | .01 | .01 | .01 | .02 | .43 | .07 | .01 | .01 | .01 | .01 | .17 | .17 | .01 | .01 | .01 | .01 | .01 | .15 |
| | | 30 | .02 | .01 | .02 | .02 | .12 | .09 | .02 | .01 | .02 | .03 | .08 | .07 | .01 | .01 | .01 | .01 | .78 | .19 | .01 | .01 | .01 | .01 | .62 | .18 |
| | | 100 | .02 | .02 | .02 | .05 | .57 | .08 | .02 | .02 | .02 | .06 | .57 | .07 | .01 | .01 | .01 | .01 | .94 | .26 | .01 | .01 | .01 | .01 | .70 | .25 |
| | 400 | 15 | .00 | .00 | .00 | .00 | .47 | .04 | .00 | .00 | .00 | .00 | .35 | .04 | .00 | .00 | .00 | .00 | .13 | .06 | .00 | .00 | .00 | .00 | .98 | .06 |
| | | 30 | .01 | .00 | .00 | .01 | .80 | .03 | .00 | .00 | .00 | .01 | .00 | .03 | .00 | .00 | .00 | .00 | .75 | .06 | .00 | .00 | .00 | .00 | .58 | .06 |
| | | 100 | .01 | .01 | .01 | .02 | .67 | .02 | .01 | .01 | .01 | .02 | .44 | .02 | .00 | .00 | .00 | .00 | .90 | .07 | .00 | .00 | .00 | .00 | .66 | .07 |
| Moderate Skew | 30 | 15 | .61 | .55 | .69 | .52 | .48 | .11 | .24 | .21 | .32 | .84 | .99 | .07 | .25 | .24 | .26 | .15 | .22 | .04 | .14 | .14 | .17 | .14 | .49 | .04 |
| | | 30 | .75 | .71 | .83 | .62 | .40 | .06 | .35 | .30 | .44 | .08 | .48 | .04 | .29 | .30 | .32 | .20 | .99 | .03 | .18 | .19 | .22 | .18 | .41 | .03 |
| | | 100 | .15 | .10 | .16 | .76 | .09 | .03 | .62 | .48 | .69 | .59 | .49 | .01 | .37 | .40 | .44 | .27 | .30 | .03 | .27 | .29 | .33 | .24 | .80 | .03 |
| | 60 | 15 | .53 | .48 | .61 | .45 | .12 | .08 | .20 | .17 | .28 | .73 | .65 | .06 | .21 | .21 | .22 | .12 | .17 | .02 | .11 | .11 | .14 | .11 | .40 | .02 |
| | | 30 | .68 | .63 | .74 | .56 | .84 | .05 | .32 | .27 | .42 | .97 | .10 | .03 | .25 | .26 | .28 | .16 | .86 | .02 | .15 | .16 | .19 | .15 | .24 | .01 |
| | | 100 | .96 | .91 | .97 | .68 | .25 | .02 | .55 | .42 | .61 | .39 | .17 | .01 | .30 | .32 | .36 | .22 | .12 | .01 | .21 | .23 | .26 | .20 | .57 | .01 |
| | 120 | 15 | .49 | .44 | .55 | .42 | .95 | .08 | .19 | .16 | .26 | .67 | .48 | .05 | .19 | .18 | .20 | .10 | .13 | .01 | .10 | .10 | .12 | .09 | .36 | .01 |

| | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 30 | .63 | .58 | .69 | .52 | .48 | .04 | .30 | .25 | .38 | .90 | .81 | .02 | .22 | .23 | .25 | .15 | .76 | .01 | .14 | .14 | .17 | .13 | .11 | .01 |
| | | 100 | .90 | .85 | .90 | .66 | .52 | .01 | .52 | .40 | .57 | .32 | .88 | .00 | .28 | .30 | .33 | .21 | .98 | .01 | .19 | .21 | .24 | .19 | .40 | .01 |
| | 400 | 15 | .47 | .42 | .53 | .39 | .80 | .07 | .18 | .15 | .25 | .63 | .34 | .05 | .17 | .17 | .19 | .09 | .10 | .00 | .09 | .09 | .11 | .09 | .32 | .00 |
| | | 30 | .59 | .54 | .65 | .49 | .15 | .04 | .29 | .24 | .37 | .84 | .56 | .02 | .21 | .21 | .23 | .14 | .73 | .00 | .12 | .13 | .15 | .12 | .07 | .00 |
| | | 100 | .85 | .80 | .85 | .63 | .90 | .01 | .50 | .39 | .55 | .28 | .62 | .00 | .26 | .28 | .31 | .19 | .94 | .00 | .18 | .19 | .22 | .17 | .33 | .00 |
| Heavy Skew | 30 | 15 | .48 | .80 | .38 | .14 | .80 | .08 | .26 | .27 | .53 | .73 | .82 | .11 | .59 | .69 | .82 | .40 | .97 | .06 | .23 | .27 | .36 | .39 | .51 | .05 |
| | | 30 | .81 | .11 | .01 | .51 | .19 | .08 | .35 | .32 | .65 | .05 | .82 | .10 | .69 | .88 | .06 | .54 | .55 | .07 | .33 | .43 | .56 | .50 | .25 | .06 |
| | | 100 | .53 | .43 | .48 | .60 | .09 | .06 | .47 | .37 | .70 | .53 | .76 | .10 | .90 | .23 | .50 | .81 | .77 | .06 | .51 | .70 | .87 | .75 | .44 | .06 |
| | 60 | 15 | .28 | .54 | .64 | .99 | .62 | .05 | .22 | .23 | .47 | .74 | .71 | .07 | .52 | .61 | .72 | .34 | .89 | .03 | .20 | .24 | .33 | .34 | .36 | .03 |
| | | 30 | .62 | .85 | .16 | .38 | .81 | .03 | .33 | .30 | .62 | .94 | .66 | .04 | .61 | .78 | .94 | .50 | .46 | .02 | .29 | .38 | .50 | .46 | .08 | .02 |
| | | 100 | .20 | .12 | .43 | .51 | .38 | .03 | .44 | .35 | .66 | 1.39 | .62 | .04 | .80 | .10 | .33 | .73 | .58 | .02 | .47 | .63 | .79 | .68 | .15 | .03 |
| | 120 | 15 | .21 | .42 | .35 | .94 | .55 | .05 | .21 | .22 | .45 | .12 | .66 | .06 | .48 | .57 | .67 | .32 | .86 | .01 | .19 | .23 | .31 | .32 | .32 | .01 |
| | | 30 | .46 | .64 | .69 | .28 | .60 | .02 | .30 | .28 | .58 | .32 | .60 | .03 | .57 | .73 | .87 | .45 | .39 | .01 | .28 | .36 | .47 | .42 | .97 | .01 |
| | | 100 | .05 | .96 | .10 | .45 | .00 | .01 | .42 | .33 | .64 | 3.47 | .54 | .02 | .75 | .02 | .23 | .68 | .44 | .01 | .44 | .60 | .75 | .63 | .94 | .01 |
| | 400 | 15 | .14 | .34 | .17 | .89 | .49 | .04 | .20 | .21 | .43 | .73 | .63 | .05 | .46 | .54 | .63 | .30 | .83 | .00 | .17 | .21 | .28 | .29 | .28 | .00 |
| | | 30 | .41 | .57 | .53 | .25 | .48 | .02 | .30 | .28 | .57 | .33 | .55 | .02 | .55 | .69 | .83 | .43 | .36 | .00 | .26 | .34 | .45 | .40 | .92 | .00 |
| | | 100 | .95 | .85 | .84 | .42 | .64 | .01 | .42 | .33 | .63 | 1.90 | .48 | .01 | .70 | .96 | .16 | .66 | .38 | .00 | .41 | .57 | .71 | .61 | .85 | .00 |

## APPENDIX G: Frequency of non-linearity and heteroscedasticity for each dispersion index across simulated conditions in normal, moderate, and heavy distributions

**Box Standard Deviation, 1 Item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 64 | | .1 | .1 |
| 0 | 291 | | .6 | .8 |
| 1 | 47516 .1 | 99.0 | 99.0 | 99.7 |
| 2 | 124 .6 | .3 | .3 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Standard Deviation, 5 Items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 68 | | .1 | .2 |
| 0 | 308 | | .6 | .8 |
| 1 | 47497 .1 | 99.0 | 99.0 | 99.7 |
| 2 | 122 .6 | .3 | .3 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Standard Deviation, 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 44209 | 92.1 | 92.1 | 92.1 |
| 1.000 | 3791 | 7.9 | 7.9 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Standard Deviation 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45072 | 93.9 | 93.9 | 93.9 |
| 1.000 | 2928 | 6.1 | 6.1 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Adm 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 44671 | 93.1 | 93.1 | 93.1 |
| 1.000 | 3329 | 6.9 | 6.9 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Adm 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 60 | .1 | .1 | .1 |
| 0 | 284 | .6 | .6 | .7 |
| 1 | 47526 | | 99.0 | 99.7 |
| 2 | 125 | | .3 | 100.0 |
| Total | 48000 | 99.0 | 100.0 | |

.3
100.0

**Box Adm 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 69 | .1 | .1 | .2 |
| 0 | 302 | .6 | .6 | .8 |
| 1 | 47504 | | 99.0 | 99.8 |
| 2 | 120 | | .3 | 100.0 |
| Total | 48000 | 99.0 | 100.0 | |

.3
100.0

**Box Admd 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 61 | .1 | .1 | .1 |

**White Adm 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45227 | 94.2 | 94.2 | 94.2 |
| 1.000 | 2773 | | 5.8 | 100.0 |
| Total | 48000 | | 100.0 | |

5.8
100.0

**White Admd 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 44457 | 92.6 | 92.6 | 92.6 |
| 1.000 | 3543 | | 7.4 | 100.0 |
| Total | 48000 | | 100.0 | |

7.4
100.0

**White Admd 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45198 | 94.2 | 94.2 | 94.2 |
| 1.000 | 2802 | | 5.8 | 100.0 |
| Total | 48000 | | 100.0 | |

5.8
100.0

**White MAD 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 43843 | 91.3 | 91.3 | 91.3 |
| 1.000 | 4157 | | 8.7 | 100.0 |

8.7

| | | | | |
|---|---|---|---|---|
| 0 | 285 | .6 | .6 | .7 |
| 1 | 47520 | | 99.0 | 99.7 |
| 2 | 129 | | .3 | 100.0 |
| Total | 48000 | | 100.0 | |

99.0
.3
100.0

**Box Admd 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 70 | .1 | .1 | .2 |
| 0 | 302 | .6 | .6 | .8 |
| 1 | 47502 | | 99.0 | 99.7 |
| 2 | 121 | | .3 | 100.0 |
| Total | 48000 | | 100.0 | |

99.0
.3
100.0

**Box MAD 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 57 | .1 | .1 | .1 |
| 0 | 279 | .6 | .6 | .7 |
| 1 | 47520 | | 99.0 | 99.7 |
| 2 | 138 | | .3 | 100.0 |
| 3 | 1 | .0 | .0 | 100.0 |
| Total | 48000 | | 100.0 | |

99.0
.3
100.0

| | | | | |
|---|---|---|---|---|
| Total | 48000 | 100.0 | 100.0 | |

**White MAD 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45432 | 94.7 | 94.7 | 94.7 |
| 1.000 | 2568 | | 5.4 | 100.0 |
| Total | 48000 | | 100.0 | |

5.4
100.0

**White awg 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 44404 | 92.5 | 92.5 | 92.5 |
| 1.000 | 3596 | | 7.5 | 100.0 |
| Total | 48000 | | 100.0 | |

7.5
100.0

**White awg 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 44531 | 92.8 | 92.8 | 92.8 |
| 1.000 | 3469 | | 7.2 | 100.0 |
| Total | 48000 | | 100.0 | |

7.2
100.0

**White CV 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45770 | 95.4 | 95.4 | 95.4 |

**Box MAD 5 items**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| Valid | -2 | 5 | .0 | .0 | .0 |
| | -1 | 63 | .1 | .1 | .1 |
| | 0 | 274 | .6 | .6 | .7 |
| | 1 | 47514 | | 99.0 | 99.7 |
| | 2 | 144 | | .3 | 100.0 |
| | Total | 48000 | | 100.0 | |

99.0

.3

100.0

**Box awg 1 item**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| | -2 | 4 | .0 | .0 | .0 |
| | -1 | 67 | .1 | .1 | .1 |
| | 0 | 276 | .6 | .6 | .7 |
| | 1 | 47512 | | 99.0 | 99.7 |
| | 2 | 140 | | .3 | 100.0 |
| | 3 | 1 | .0 | .0 | 100.0 |
| | Total | 48000 | | 100.0 | |

99.0

.3

100.0

**Box awg 5 items**

| | | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|---|
| | -2 | 6 | .0 | .0 | .0 |

| | | | | |
|---|---|---|---|---|
| 1.000 | 2230 | 4.6 | 4.6 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White CV 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45698 | 95.2 | 95.2 | 95.2 |
| 1.000 | 2302 | | 4.8 | 100.0 |
| Total | 48000 | | 100.0 | |

4.8

100.0

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -1 | 59 | .1 | .1 | .1 |
| 0 | 298 | .6 | .6 | .8 |
| 1 | 47501 | | 99.0 | 99.7 |
| 2 | 136 | | .3 | 100.0 |
| Total | 48000 | 99.0 | 100.0 | |

.3 100.0

**Box CV 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 87 | .2 | .2 | .2 |
| 0 | 311 | .6 | .6 | .8 |
| 1 | 47488 | | 98.9 | 99.8 |
| 2 | 109 | | .2 | 100.0 |
| Total | 48000 | 98.9 | 100.0 | |

.2 100.0

**Box awg 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 62 | .1 | .1 | .1 |
| 0 | 280 | .6 | .6 | .7 |
| 1 | 47514 | | 99.0 | 99.7 |
| 2 | 139 | | .3 | 100.0 |
| Total | 48000 | 99.0 | 100.0 | |

.3 100.0

## APPENDIX H: Frequency of non-linearity and heteroscedasticy for each dispersion index across simulated conditions in moderately skewed distribution

**Box Standard Deviation 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 7 | .0 | .0 | .0 |
| -1 | 80 | | .2 | .2 |
| 0 | 342 | | .7 | .9 |
| 1 | 47464 .2 | 98.9 | 98.9 | 99.8 |
| 2 | 107 .7 | .2 | .2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Standard Deviation 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 81 | | .2 | .2 |
| 0 | 324 | | .7 | .9 |
| 1 | 47478.2 | 98.9 | 98.9 | 99.8 |
| 2 | 112.7 | .2 | .2 | 100.0 |

**White Standard Deviation 1 Item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45956 | 95.7 | 95.7 | 95.7 |
| 1.000 | 2044 | 4.3 | 4.3 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Standard Deviation 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45694 | 95.2 | 95.2 | 95.2 |
| 1.000 | 2306 | 4.8 | 4.8 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Adm 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45978 | 95.8 | 95.8 | 95.8 |

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| Total | 48000 | 100.0 | 100.0 | |

**Box adm 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 7 | .0 | .0 | .0 |
| -1 | 75 | .2 | .2 | .2 |
| 0 | 334 | .7 | .7 | .9 |
| 1 | 47475 | | 98.9 | 99.8 |
| 2 | 109 | | .2 | 100.0 |
| Total | 48000 | | 100.0 | |

98.9

.2
100.0

**Box adm 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 80 | .2 | .2 | .2 |
| 0 | 323 | .7 | .7 | .9 |
| 1 | 47475 | | 98.9 | 99.8 |
| 2 | 117 | | .2 | 100.0 |
| Total | 48000 | | 100.0 | |

98.9

.2
100.0

**Box admd 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| 1.000 | 2022 | 4.2 | 4.2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Adm 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45756 | 95.3 | 95.3 | 95.3 |
| 1.000 | 2244 | | 4.7 | 100.0 |
| Total | 48000 | | 100.0 | |

4.7
100.0

**White Admd 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 46050 | 95.9 | 95.9 | 95.9 |
| 1.000 | 1950 | | 4.1 | 100.0 |
| Total | 48000 | | 100.0 | |

4.1
100.0

**White Admd 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45790 | 95.4 | 95.4 | 95.4 |
| 1.000 | 2210 | | 4.6 | 100.0 |
| Total | 48000 | | 100.0 | |

4.6
100.0

**White MAD 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 7 | .0 | .0 | .0 |
| -1 | 85 | .2 | .2 | .2 |
| 0 | 351 | .7 | .7 | .9 |
| 1 | 47454 | | 98.9 | 99.8 |
| 2 | 103 | | .2 | 100.0 |
| Total | 48000 | 98.9 | 100.0 | |

.2
100.0

**Box admd 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 79 | .2 | .2 | .2 |
| 0 | 324 | .7 | .7 | .9 |
| 1 | 47476 | | 98.9 | 99.8 |
| 2 | 115 | 98.9 | .2 | 100.0 |
| Total | 48000 | | 100.0 | |

.2
100.0

**Box MAD 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 77 | .2 | .2 | .2 |
| 0 | 325 | .7 | .7 | .9 |
| 1 | 47480 | | 98.9 | 99.8 |

98.9

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45339 | 94.5 | 94.5 | 94.5 |
| 1.000 | 2661 | | 5.5 | 100.0 |
| Total | 48000 | | 100.0 | |

5.5
100.0

**White MAD 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45852 | 95.5 | 95.5 | 95.5 |
| 1.000 | 2148 | | 4.5 | 100.0 |
| Total | 48000 | | 100.0 | |

4.5
100.0

**White awg 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 46497 | 96.9 | 96.9 | 96.9 |
| 1.000 | 1503 | | 3.1 | 100.0 |
| Total | 48000 | | 100.0 | |

3.1
100.0

**White awg 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 47154 | 98.2 | 98.2 | 98.2 |
| 1.000 | 846 | | 1.8 | 100.0 |
| Total | 48000 | | 100.0 | |

1.8
100.0

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| 2 | 112 | .2 | .2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box MAD 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 65 | .1 | .1 | .1 |
| 0 | 297 | .6 | .6 | .8 |
| 1 | 47503 | | 99.0 | 99.7 |
| 2 | 130 | | .3 | 100.0 |
| Total | 48000 | | 100.0 | |

99.0
.3
100.0

**Box awg 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 54 | .1 | .1 | .1 |
| 0 | 252 | .5 | .5 | .7 |
| 1 | 47544 | | 99.1 | 99.7 |
| 2 | 144 | | .3 | 100.0 |
| Total | 48000 | | 100.0 | |

99.1
.3
100.0

**Box awg 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|

**White CV 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45378 | 94.5 | 94.5 | 94.5 |
| 1.000 | 2622 | | 5.5 | 100.0 |
| Total | 48000 | | 100.0 | |

5.5
100.0

**White CV 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45847 | 95.5 | 95.5 | 95.5 |
| 1.000 | 2153 | | 4.5 | 100.0 |
| Total | 48000 | | 100.0 | |

4.5
100.0

| | | | | |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 59 | .1 | .1 | .1 |
| 0 | 282 | .6 | .6 | .7 |
| 1 | 47502 | | 99.0 | 99.7 |
| 2 | 152 | | .3 | 100.0 |
| Total | 48000 | 99.0 | 100.0 | |

.3 100.0

**Box CV 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 9 | .0 | .0 | .0 |
| -1 | 81 | .2 | .2 | .2 |
| 0 | 351 | .7 | .7 | .9 |
| 1 | 47465 | | 98.9 | 99.8 |
| 2 | 94 | | .2 | 100.0 |
| Total | 48000 | 98.9 | 100.0 | |

.2 100.0

**Box CV 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 70 | .1 | .1 | .2 |
| 0 | 294 | .6 | .6 | .8 |
| 1 | 47497 | | 99.0 | 99.7 |
| 2 | 134 | | .3 | 100.0 |
| Total | 48000 | 99.0 | 100.0 | |

.3 100.0

## APPENDIX I: Frequency of non-linearity and heteroscedasticy for each dispersion index across simulated conditions in heavy skewed distribution

**Box Standard Deviation 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 82 | .2 | .2 | .2 |
| 0 | 314 | .7 | .7 | .8 |
| 1 | 47488 | 98.9 | 98.9 | 99.8 |
| 2 | 111 | .2 | .2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Standard Deviation 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 75 | .2 | .2 | .2 |
| 0 | 310 | .6 | .6 | .8 |
| 1 | 47497 | 99.0 | 99.0 | 99.8 |

**White Standard Deviation 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45947 | 95.7 | 95.7 | 95.7 |
| 1.000 | 2053 | 4.3 | 4.3 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Standard Deviation 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45578 | 95.0 | 95.0 | 95.0 |
| 1.000 | 2422 | 5.0 | 5.0 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Adm 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45924 | 95.7 | 95.7 | 95.7 |

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| 2 | 112 | .2 | .2 | 100.0 |
| 3 | 1 | .0 | .0 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Adm 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 84 | .2 | .2 | .2 |
| 0 | 338 | .7 | .7 | .9 |
| 1 | 47467 | 98.9 | 98.9 | 99.8 |
| 2 | 105 | .2 | .2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Adm 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 76 | .2 | .2 | .2 |
| 0 | 302 | .6 | .6 | .8 |
| 1 | 47506 | 99.0 | 99.0 | 99.8 |
| 2 | 110 | .2 | .2 | 100.0 |
| 3 | 1 | .0 | .0 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| 1.000 | 2076 | 4.3 | 4.3 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Adm 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45650 | 95.1 | 95.1 | 95.1 |
| 1.000 | 2350 | 4.9 | 4.9 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Admd 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45779 | 95.4 | 95.4 | 95.4 |
| 1.000 | 2221 | 4.6 | 4.6 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White Admd 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45742 | 95.3 | 95.3 | 95.3 |
| 1.000 | 2258 | 4.7 | 4.7 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White MAD 1 item**

**Box Admd 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 7 | .0 | .0 | .0 |
| -1 | 76 | .2 | .2 | .2 |
| 0 | 312 | .7 | .7 | .8 |
| 1 | 47489 | 98.9 | 98.9 | 99.8 |
| 2 | 116 | .2 | .2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**Box Admd 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 75 | .2 | .2 | .2 |
| 0 | 310 | .6 | .6 | .8 |
| 1 | 47499 | 99.0 | 99.0 | 99.8 |
| 2 | 110 | .2 | .2 | 100.0 |
| 3 | 1 | .0 | .0 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**/Box MAD 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45484 | 94.8 | 94.8 | 94.8 |
| 1.000 | 2516 | 5.2 | 5.2 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White MAD 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45612 | 95.0 | 95.0 | 95.0 |
| 1.000 | 2388 | 5.0 | 5.0 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White awg 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 46200 | 96.3 | 96.3 | 96.3 |
| 1.000 | 1800 | 3.8 | 3.8 | 100.0 |
| Total | 48000 | 100.0 | 100.0 | |

**White awg 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 46752 | 97.4 | 97.4 | 97.4 |
| 1.000 | 1248 | 2.6 | 2.6 | 100.0 |

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 54 | .1 | .1 | .1 |
| 0 | 242 | .5 | .5 | .6 |
| 1 | 47538 | | | 99.7 |
| 2 | 161 | .3 | .3 | 100.0 |
| Total | 48000 | 99.0 | 99.0 | |

100.0 100.0

**Box MAD 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 67 | .1 | .1 | .2 |
| 0 | 278 | .6 | .6 | .7 |
| 1 | 47521 | | | 99.7 |
| 2 | 128 | .3 | .3 | 100.0 |
| Total | 48000 | 99.0 | 99.0 | |

100.0 100.0

**Box awg 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 52 | .1 | .1 | .1 |
| 0 | 265 | .6 | .6 | .7 |
| 1 | 47529 | | | 99.7 |

99.0 99.0

| | | | | |
|---|---|---|---|---|
| Total | 48000 | 100.0 | 100.0 | |

**White CV 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45423 | 94.6 | 94.6 | 94.6 |
| 1.000 | 2577 | 5.4 | | 100.0 |
| Total | 48000 | 100.0 | | |

5.4
100.0

**White CV 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| .000 | 45796 | 95.4 | 95.4 | 95.4 |
| 1.000 | 2204 | 4.6 | | 100.0 |
| Total | 48000 | 100.0 | | |

4.6
100.0

| | | | | |
|---|---|---|---|---|
| 2 | 148 | .3 | .3 | 100.0 |
| 3 | 1 | .0 | .0 | 100.0 |
| Total | 48000 | | | |

100.0 100.0

**Box awg 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 5 | .0 | .0 | .0 |
| -1 | 55 | .1 | .1 | .1 |
| 0 | 247 | .5 | .5 | .6 |
| 1 | 47534 | | | 99.7 |
| 2 | 158 | .3 | .3 | 100.0 |
| 3 | 1 | 99.0 .0 | 99.0 .0 | 100.0 |
| Total | 48000 | | | |

100.0 100.0

**Box CV 1 item**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 83 | .2 | .2 | .2 |
| 0 | 349 | .7 | .7 | .9 |
| 1 | 47473 | | | 99.8 |
| 2 | 89 | .2 | .2 | 100.0 |
| Total | 48000 | 98.9 | 98.9 | |

100.0 100.0

**Box CV 5 items**

| | Frequency | Percent | Valid Percent | Cumulative Percent |
|---|---|---|---|---|
| -2 | 6 | .0 | .0 | .0 |
| -1 | 68 | .1 | .1 | .2 |
| 0 | 306 | .6 | .6 | .8 |
| 1 | 47497 | | | 99.7 |
| 2 | 123 | .3 | .3 | 100.0 |
| Total | 48000 | 99.0 | 99.0 | |
| | | 100.0 | 100.0 | |

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